



Kaunas University of Technology

School of Economics and Business

Insolvency Risk Assessment of Companies Listed on the NASDAQ Baltic Stock Exchange

Master's Final Degree Project

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Accounting and Auditing (6211LX037)

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Summary

The main aim of this Master's thesis is to assess the insolvency risk of selected companies listed on the NASDAQ Baltic Stock Exchange and to determine which methods are the most appropriate for risk assessment, using such secondary tasks as the analysis of existing methods for insolvency assessment, the development of empirical research methodology.

This work consists of four main parts: problem analysis, review of the scientific literature, research and its results, conclusions and recommendations.

The problem analysis reviews the concept of insolvency, the positive and negative consequences of insolvency, and proves the need for insolvency risk assessment. The analysis of scientific literature examines the opinion of different authors related to the insolvency assessment methods, compares the proposed methodologies, reviews each of the stages proposed for use in insolvency risk assessment. Internal and external factors that determine the company's solvency are being analysed, financial indicators that are the most appropriate for assessing the company's financial condition from the perspective of insolvency are identified, as well as the possible use of bankruptcy forecasting models as an additional tool to determine potential insolvency risk is described and one of the newer methods - Kralicek tests. Finally, a summary of the analysed information is presented using a conceptual model.

After the analysis of the scientific literature, the author describes the methodology of the insolvency risk assessment research, proposing to research in 6 stages. The author indicates how the companies will be selected for a study, what economic indicators are examined in order to assess their impact on the total number of insolvent companies. In addition, the selection of financial indicators and other models that can help assess the risk of corporate insolvency is performed and the necessity of using these models is justified.

The study found that factors such as unemployment and inflation have the greatest impact on the number of insolvent companies. Also, during the research, the limitation of the use of financial indicators was determined, which is defined by several factors: the problem of complex evaluation of indicator values and the objectivity of the analyzer. The use of the Kralicek DF indicator and its application together with financial indicators showed good results during the study, which led to the conclusion that this method is suitable for a complex insolvency risk assessment. The use of bankruptcy prediction models in the study allowed the author to identify the shortcomings and limitations of these models, comparing the results of different models, decide which models are more suitable for the Baltic market and which do

not show obvious financial difficulties previously identified using other insolvency assessment methodologies.

The conclusions and recommendations summarize the main concepts of the analysis of the scientific literature and the results of the research. The author believes that the results of the study could provide useful information on the topic of insolvency analysis for companies and other stakeholders, such as investors interested in Baltic equities.

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Santrauka

Pagrindinis šio magistro baigiamojo darbo tikslas įvertinti pasirinktų įmonių, listinguojamų NASDAQ Baltic vertybinių popierių biržoje, nemokumo riziką, bei nustatyti kokie metodai yra tinkamiausi rizikos įvertinimui, pasitelkus tokius pagalbinius uždavinius kaip jau naudojamų metodų nemokumo vertinimui analize, empirinio tyrimo metodologijos kūrimas.

Šį darbą sudaro keturios pagrindinės dalys: problemos analizė, mokslinės literatūros apžvalga, tyrimas ir jo rezultatai, išvados ir pasiūlymai.

Problemos analizė apžvelgia nemokumo sampratą, teigiamas ir neigiamas nemokumo pasekmes bei pagrindžia nemokumo rizikos vertinimo būtinybę. Mokslinės literatūros analizė vertina skirtingų autorių nuomonę nemokumo vertinimo metodų atžvilgiu, lygina siūlomas naudoti metodologijas, apžvelgia kiekvieną iš etapų, siūlomų naudoti nemokumo rizikos vertinimui. Analizuojami vidiniai ir išoriniai veiksniai, lemiantis įmonės mokumą, nustatoma kokie finansiniai rodikliai tinkamiausi atliekant įmonės finansinės būklės vertinimą, žiūrint iš nemokumo perspektyvos, taip pat aprašomas galimas bankroto prognozavimo modelių, kaip papildomos priemonės nustatant galimą nemokumo riziką, naudojimas bei vienas naujesnių metodų – Kralicek testai. Pabaigoje pateikiamas išanalizuotos informacijos apibendrinimas, pasitelkus konceptualųjį modelį.

Po mokslinės literatūros analizės autorius aprašo nemokumo rizikos vertinimo tyrimo metodologiją, siūlydamas atlikti tyrimą 6 etapais. Autorius nurodo kaip bus atrenkamos įmonės, dalyvaujančios tyrime, kokie ekonominiai rodikliai tiriami, norint įvertinti jų įtaką bendram nemokių įmonių skaičiui. Papildomai vykdoma finansinių rodiklių bei kitų modelių, galinčių padėti įvertinti įmonių nemokumo riziką, atranka bei pagrindžiamas šių modelių naudojimo būtinumas.

Atliktas tyrimas leido nustatyti, jog didžiausią įtaką nemokių įmonių skaičiui turi tokie veiksniai kaip nedarbo ir infliacijos lygis. Taip pat tyrimo metu buvo nustatytas finansinių rodiklių naudojimo ribotumas, kurį lemia keli veiksniai: rodiklių reikšmių kompleksinio vertinimo problema bei analizuojančio asmens objektyvumas. Tyrimo metu gerus rezultatus parodė Kralicek DF indikatoriaus naudojimas bei jo pritaikymas kartu su finansiniais rodikliais, tai leido padaryti išvadą, jog šis metodas yra tinkamas kompleksiniam nemokumo rizikos vertinimui. Bankroto prognozavimo modelių naudojimas tiriamajame darbe leido nustatyti šių modelių trūkumus bei apribojimus, palyginus skirtingu modelių rezultatus, buvo nustatyta kurie modeliai yra tinkamesni Baltijos šalių rinkai, o kurie neparodo

akivaizdžių įmonių finansinių sunkumų, jau anksčiau nustatytų naudojant kitas nemokumo vertinimo metodikas.

Išvadose ir pasiūlymuose apibendrinamos pagrindinės mokslinės literatūros analizės sampratos bei atlikto tyrimo rezultatai. Autorius mano, kad tyrimo rezultatai galėtų suteikti naudingos informacijos nemokumo analizės tema įmonėms bei kitoms suinteresuotoms šalims, tokioms kaip investuotojai, besidominantys Baltijos šalių akcijomis.

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Introduction

Nowadays as the level of private debt is increasing in several EU countries, this prevents companies and households from undertaking new investments and lowers the level of their consumption, creating a situation of debt loom. If private debt levels remain high, economic activity typically struggles to accelerate. The persistence of high debt can be explained first by the low inflation-low growth environment that has made servicing existing loan obligations more difficult in most EU countries. Faced with these challenges, companies are more likely to become insolvent.

Insolvency risk can be identified as the risk that a company will be incapable to satisfy its obligations. Also, it is known as bankruptcy risk. The failure of a business has an impact not only on a company owner, but it also affects other parties who is related to a failed company: employees, creditors, other businesses, and even competitors. However, businesses do not become insolvent overnight. The ability of a business's management to detect and correct existing flaws, or, at the very least, the methods used to prevent the substantial negative effects that generate biases, is critical to its success. Typically, there are several insolvency warnings that indicate the start of the financial problems of a company. In the international economy, in the unstable environment, the consequences of a company's insolvency risk lead to a slew of operational and strategic challenges. Companies in financial distress typically live hand-to-mouth, paying their bills late or not at all. If a company is constantly chasing a customer for money, it could be a sign of serious cashflow issues. The accuracy of information used to support management decisions, as well as the risk management system developed at the entity level, play an important role in avoiding the difficult situations that most businesses face. As a result, it is critical to investigate the phenomenon of insolvency, the factors that influence it, and opportunities to reduce the risk of this problem.

The **research novelty** – insolvency risk assessment methods, could help companies to predict difficulties, which company could face in the future. The vast majority of the researches on insolvency assessment topic use the bankruptcy prediction models to assess the risks. However, these models mainly were developed in the middle of XX century by Z.Altman and other researchers. The main issue is to find out if there are other methodologies for the insolvency risk assessment that combine the different ways of risk assessment.

The **aim of the research** is to analyze phenomenon of insolvency and related its assessment methods suitable for insolvency risk assessment.

The main **research questions** are:

- What is insolvency?
- Which methods for insolvency assessment are currently used?

Key **research objectives** are:

1. To describe insolvency concept and its key types, to justify the importance and need of insolvency risk assessment;
2. To review and systematize other methods used for financial and non-financial risk assessment, as well as to analyze previous studies on corporate insolvency and the risk of bankruptcy;

3. To develop a methodology for empirical research of insolvency risk assessment;
4. To conduct an empirical research based on data of publicly listed companies on the NASDAQ Baltic stock exchange.

Research methodology: The research will be conducted in four steps. The first step is to identify the meaning of insolvency, then to analyze the problem of insolvency risk assessment in current environment. The second step will cover scientific literature analysis, comparing the works of different authors, group them corresponding to similarities found. Scientific literature analysis will help to identify the gap in scientific literature on insolvency assessment topic. The third step is to develop an insolvency risk assessment methodology for the empirical research. The latest step is the research on insolvency risk assessment for companies listed on The NASDAQ Baltic stock exchange.

1. Insolvency risk assessment problem analysis

1.1. Insolvency concept and types

The concept of insolvency and the first insolvency procedures appeared long ago before the time of the Roman empire. Gratzer (2006) explains that a legal procedure was established to regulate the relationship between insolvent debtors and creditors. A fundamental aspect of this regulatory system was that the creditor had the right to accrue life and property of an insolvent debtor. In that case, the debtor was the primary target of the restraint. This execution of the creditor inevitably led to the execution of the debtor's property (the execution of tangible assets) becoming the primary goal of the distraint. This shift in emphasis from execution of the person to execution of tangible assets lasted several hundred years and can be divided into at least two phases: 1) the proceedings in older Roman law according to the Twelve Tables, and 2) a weakening of creditors' power via *lex poetelia* and *lex Julia*.

Nowadays, there are two key types of insolvency: corporate and personal. The “concept of personal insolvency is new enough in legal terminology and was described precisely only in 2013 when the Law for Natural Persons Bankrupt came into force in Lithuania” (Jurevičienė and Sukačevskytė, 2014). Personal insolvency is defined as the “condition of a natural person when he/she is unable to fulfil the debt obligations whose terms have expired and the amount of which exceeds 25 minimum monthly wages approved by the Government of the Republic of Lithuania” (LR Law for Natural persons Bankrupt, 2013).

Corporate insolvency is mostly defined in law and related acts. It worth to mention that the term insolvency and bankruptcy are other confused, even in the legal acts. Initially, bankruptcy was defined by LR Law on Companies bankrupt in 2011 as following: “the state of the company, when it does not settle with the creditor (creditors) three months after the deadline set by law, other legal acts, as well as the obligations of the creditor and the company to fulfil the obligations of the company, or after the same deadline after the creditor/creditor's obligation to fulfil obligations the maturity was not fixed, and the overdue liabilities (debts) of the company exceed half of the value of the assets entered in its balance sheet”. It requires that companies seeking to prevent bankruptcy must be solvent, that means to have enough payment tools to settle short-term and long-term obligations. Mackevičius, Šneidere, Tamulevičienė (2018) explain that as payment instruments are considered cash and cash equivalents, amounts receivable, inventories, work in progress, finished goods, goods for resale, contracts in progress, prepayments for suppliers, other current assets. These payment instruments could be used to settle short-term and long-term liabilities.

Later, in 2020 the new LR Law on Insolvency of Legal Entities entered into force and the term bankruptcy was replaced with term insolvency, with a following definition: “Insolvency of legal entity - the status of a legal person, when the legal person is unable to fulfil its property obligations in time or the obligations of the legal person exceed the value of its property” (LR Law on Insolvency, 2020).

It is visible that term insolvency and bankruptcy are very related, or even the bankruptcy can be identified as the latest step of an insolvency. The main differences between those two terms are identified in Table 1.

Table 1. Insolvency and bankruptcy differences (designed by author)

Insolvency	Bankruptcy
Potentially revocable	Cannot be revoked
Can lead to bankruptcy	Financial last possibility
Can be managed by a company	Court managed

It is worth noting that insolvency is the most recent step in the timeline of distressed debt. The first time a debtor notices the signs of difficulty in servicing debt, the timeline of troubled debt begins. This timeline begins with genuine default and insolvency and finishes when debtors are released from all obligations. At each stage of the timeline, different techniques can be used to ensure that debt is serviced or resolved quickly. As a result, an economy's outstanding stock of debt is a mix of solvent debt and debt in various stages of distress, showed in Fig. 1.

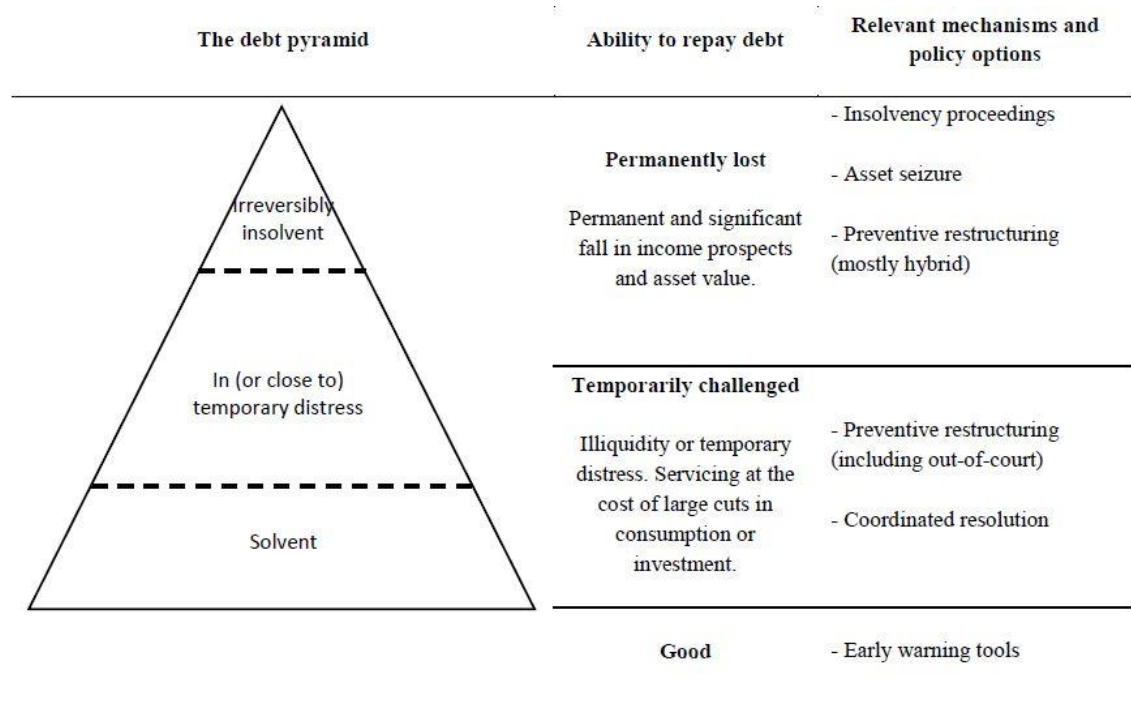
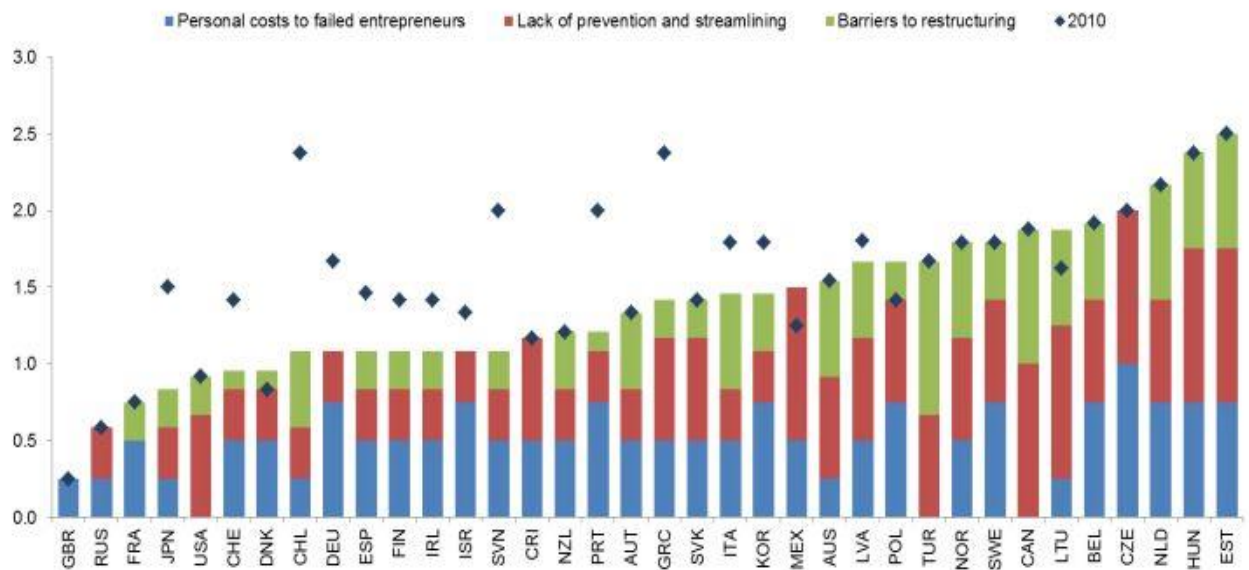


Fig. 1. Debt distress and insolvency (Macroeconomic Relevance of Insolvency Frameworks in a High-debt Context: An EU Perspective, 2016)

Insolvency frameworks vary greatly depending on the country, the legal system of the country, the key characteristics of the financial market, and monetary policy. The definition of “insolvency” varies according to jurisdiction. The existence and features of a sequence of steps, rules, and processes are required for the design of insolvency frameworks.

In the year 2018, the working papers on the Design of Insolvency regimes across counties were released by OECD. The research was conducted on the combination of three sub-indicators of insolvency regimes – personal cost to failed entrepreneurs, lack of prevention and streamlining and barriers to restructuring. Figure 2 shows the results of conducted research.



Note: The stacked bars correspond to three subcomponents of the insolvency indicator in 2016. The diamond corresponds to the value of the aggregate insolvency indicator based on these three subcomponents in 2010. Only countries for which data are available for the three sub-components in 2016 are included.
Source: Calculations based on the OECD questionnaire on insolvency regimes.

Fig. 2. OECD indicator of insolvency regimes (OECD Design of Insolvency regimes across counties, 2018)

It could be seen, that in Lithuania according to the respondents of the questionnaire is a lack of prevention and streamlining actions related to the insolvency state. As well as the barriers to restructuring business are meaningful. According to Jokubauskas R. (2017), pre-insolvency proceedings are juridical proceedings, which are created to rescue the business. This procedure can be divided into two main groups:

1. Workout supporting proceedings. This procedure includes few tools for bargaining over debt and does not affect all creditors (shareholders). Only some creditors are involved. The insolvency threshold test is not applicable;
2. Restructuring proceedings. This procedure includes numerous dispute resolution methods, and all of the creditors are involved. An insolvency threshold test is applicable (an insolvent debtor does not usually have the right to commence this procedure).

At the same time, some countries perform well only in certain aspects of insolvency regimes. For example, Canada, Turkey and Australia combine the lowest personal costs to entrepreneurial failure with the highest barriers to restructuring, while the opposite is valid in the Czech Republic, Israel, Germany and Portugal.

The analysis provided above shows that there is a confusion between term insolvency and bankruptcy, however, nowadays the term bankruptcy is often replaced by a term insolvency. In some countries the term bankruptcy is still being used for the legal procedures. Generally, the term bankruptcy is applicable mostly to describe the legal process when a company goes under the liquidation process because it cannot repay its debts, though, the term insolvency is applicable to describe the financial state of the company

when it cannot pay the debts that are due. However, the insolvent company will not necessarily go bankrupt.

1.2. Consequences of corporate insolvency

Nemec (2015) explains that bankruptcy and insolvency of the enterprises has significant impacts on the economy. Although these processes can be treated as those helping to clean up the markets, they may influence consequences on healthy enterprises as well. The consequences of corporate insolvency are typically frustrating, they result not only in the liquidation of the company, but have a further impact on its employees, other companies, the state, and society. The main socio-economic consequences referring to Grybinenko (2017), Burksaitiene (2011), Mackevicius (2018) can be defined as follows:

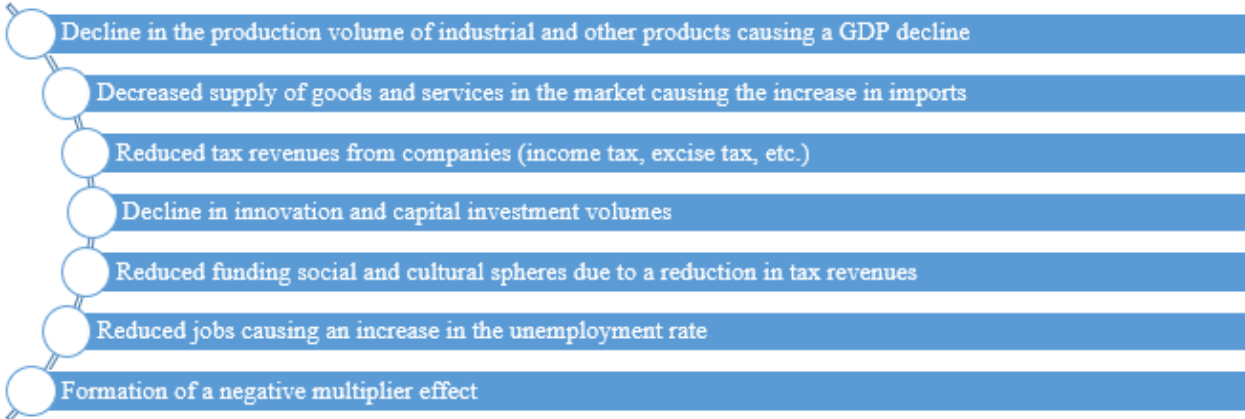


Fig. 3. Socio-economic consequences of corporate insolvency (designed by author based on Grybinenko, 2017; Bruksaitiene, 2011; Mackevicius, 2018)

The figure above clearly shows that corporate insolvency harms the overall economy of the country. It starts with a reduction in a number of companies and causes a decline in overall volume of production which harmfully affects the country’s GDP and especially GDP per capita, moreover, the supply of commodities in the market decreases substantially. Commodity price decreases may lead to increased reliance on imports. There has been a decline in capital investment in terms of accumulative values, as well as a partial drop in the rankings of doing business in the country. Technically, a decrease in a company's production volumes may affect tax deductions to the state budget and, as a result, budget expenditures. It is worth noting that major company insolvencies add pressure to supply chains. There is a risk that clients' supply chains will be disrupted, forcing them to seek out costly alternatives quickly, as well as a financial risk for their own suppliers by failing to pay them - forcing them to engage in lengthy and costly legal proceedings. The greater the size of the company declaring bankruptcy, the greater the risk of a domino effect. Furthermore, the labor market situation has become burdened, and a drop in purchasing power may be observed. These tendencies have a negative socioeconomic multiplier effect.

It is common to think about corporate insolvency negatively, however, some authors Bruksaitiene (2011), Mackevicius (2018) identify the positive effects of corporate insolvency. The positive aspects of insolvency phenomenon are mainly related to replacement of old companies with new ones, using innovative technologies and modern forms of organization. Furthermore, the situation in which

enterprises become insolvent but are not replaced by new ones should be regarded as dangerous to the national economy. Thus, insolvency could be defined as a process that allows for increased market competitiveness by eliminating unsuccessful entrepreneurs who evade or are unable to pay creditors and replacing them with new enterprises that are capable of working effectively and fulfilling their obligations. However, the situation is much better when enterprises can survive and benefit the state and society. Insolvency, as a positive phenomenon, purifies the market of unproductive enterprises, promoting technical and economic improvement; however, there is a risk of dismissing redundant employees, unused capacity, and refusing others. Additionally, insolvency could have a positive influence on the economy by allowing debtors to get out of debt, even if it has some disadvantages for the individual or enterprise going through it. This provides some security in case unexpected difficulties occur, which makes borrowing money a slightly less risky for consumers and enterprises. This enables borrowing to stimulate the economy through buying goods or services, property and equipment or taking risks in business. Creditors also feel more secure because they know having a last recourse in case their debtors are unable to fulfil obligations, so they feel more protected in providing riskier loans.

Typically, the main outcome of corporate insolvency is the liquidation of a company, which results both in negative and positive consequences for the employees, shareholders, and overall economy. Yet, the state of insolvency could possibly be a growth factor for a company as well, in case if a company does not start a procedure of a bankruptcy but overcomes the state insolvency by using appropriate anti-crisis management techniques.

1.3. The importance of insolvency risk assessment

The effect of the global recession is exceptional, harshly affecting most the world's developed economies. There is no difference if these economies are still in a state of chaos or have started a recovery stage, businesses around the world stay careful in managing their debts, and credit overall remains tight. According to Honsberger (1972) sometimes insolvency could be “a result of some sudden disaster such as fire, flood or theft by an employee. More often it is the result of a gradual deterioration in a debtor's ability to pay his debts”. A common sequence of events is for a debtor to avoid making payments or become unable to pay his debts when they become due. The enterprise becomes insolvent in the sense of balance insolvency as a result of its loss of credit as a result of his failure to pay. Thus, real or apparent insolvency on the part of a debtor, which is usually manifested as a cessation of payments, is the starting point beginning of the road that usually leads to bankruptcy.

Nowadays, the COVID-19 pandemic can be identified as the sudden disaster, which can lead to drastically increased number of insolvencies soon. The outbreak of the coronavirus though is compounding the challenges to global trade and manufacturing and causing disruption to global supply chains. The Euler Hermes Economic Research (2020) analysts are already expecting the rise of global business insolvencies before the COVID-19 crisis stuck, as a result of a slowing rate of economic growth and the lingering impact of trade wars, political uncertainty, and social tensions, as well as a long-standing gap between the manufacturing and service sectors. The global economy was then hit by the COVID-19, and analysts predict that the majority of insolvencies will occur between the end of 2020 and the first half of 2021, as a result of difficult initial conditions, as well as contrary re-opening strategies

and alternative policy measures, which mostly relate to when insolvencies are filed. The Fig. 4 provided below shows the changes in insolvencies by 2021 compared to 2019.

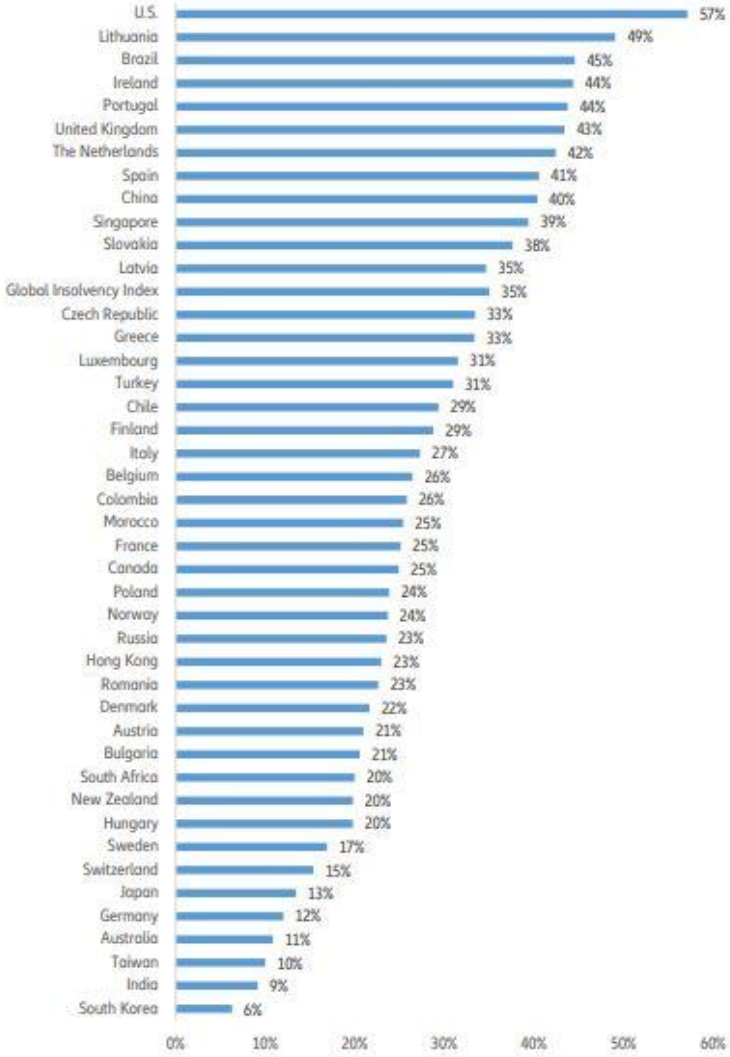


Fig. 4. Changes in insolvencies by 2021 (2021 level compared to 2019 level in %) (Euler Hermes Economic Research, 2020)

Fig. 4 shows that 12 countries, including two Baltic States: Lithuania and Latvia are above the Global insolvency index, which shows an average increase of corporate insolvency by 35%, it means that the number of possible corporate insolvencies will be higher than the world’s average. In Lithuania possible number of corporate insolvencies can increase by 49% in 2021, considering that in 2019 the number of corporate insolvencies according to the Statistics Lithuania was 1608, it can be expected approximately 2396 new bankruptcy processes in 2021.

The Fig. 5 shows the Global heat map, with respect to the changes in corporate insolvencies in comparison with year 2009, when the Global financial crisis started, and number of corporate insolvencies increased rapidly, and the year 2019 when the COVID-19 pandemic began.



Fig. 5. The heat map of insolvencies by 2021 (Euler Hermes Economic Research, 2020)

Considering the Baltic States, in Lithuania the expected number of corporate insolvencies can be 0%-50% above the 2009 levels, however, at the same time 20%-40% above 2019 levels, in Latvia the expected number of corporate insolvencies can be also 20%-40% higher than in 2019, on the other hand, it will still be more than 50% below 2009 levels. In Estonia, the expected number of insolvencies, comparing with year 2009 is 50% lower, however, in comparison with year 2019, it can increase by 40%.

Performed secondary data analysis lets affirm, that problem of insolvency assessment is important to most of the European countries, especially for countries with growing economies.

The analysis of an insolvency risk assessment problem shows that this problem is common for all the economies as the insolvency as an issue itself, causes the negative consequences for an overall economy. Apparently, the insolvency regulations play an important role, however, the more vital thing is the possibility to identify the risk of an insolvency in advance. The assessment of an insolvency risk should cover the search for a general methodology, identification of main factors influencing company's performance as well an investigation of a methods that could help to assess the risk.

2. Theoretical background for the insolvency risk assessment

2.1. General methodology of corporate insolvency risk assessment

Corporate insolvency has a huge impact in the field of finance as well as for the economics of a country. The prominent institutions for a stable and prosperous business world are policymakers, investors, administrators, customers, and shareholders. The failure of a company is a global problem. To stimulate growth all over the country, some tools should be available to predict the number of companies that may fail due to insolvency. The consequences raised by the corporate insolvencies motivate the researchers to carry out work in this direction. For accounting and finance research the insolvency assessment technique is a broad area. As states Kubenka (2019), it is critical to avoid insolvency in one's own business or that of a business partner. Insolvency can often be avoided or, at the very least, losses can be minimized if the impending insolvency is detected in advance.

Dzikevicius (2015) suggests using the four-step integrated insolvency prediction model (Fig. 6), which includes not only calculation of certain ratios, but also analysis of the external and internal environment, as well as a general financial health check of the enterprise.

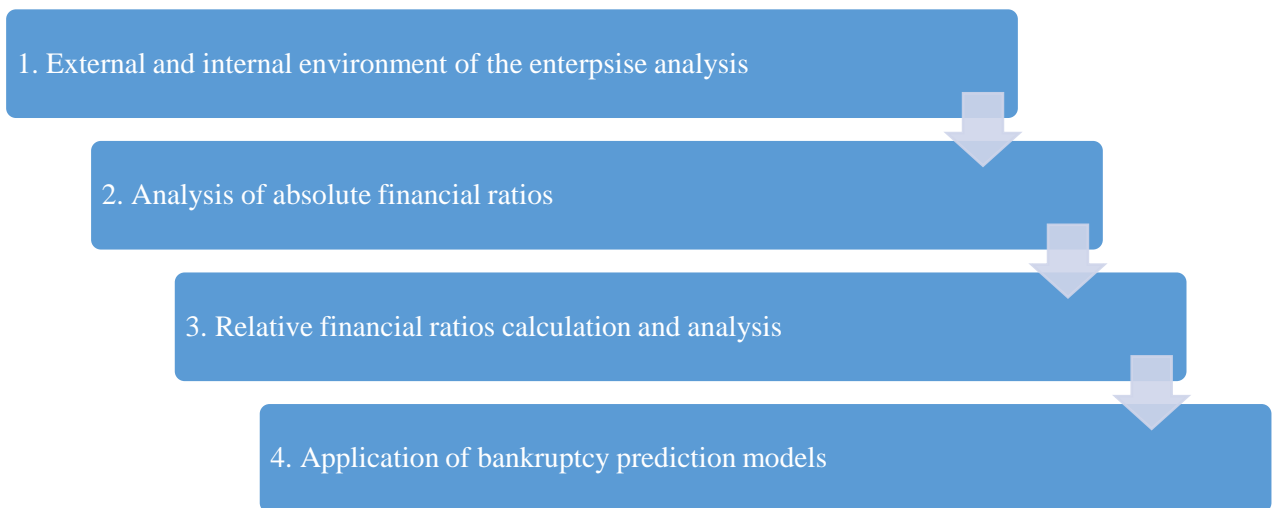


Fig. 6. Integrated enterprise insolvency prediction model (Dzikevicius, 2015)

Dzikevicius (2015) recommends starting an enterprise insolvency assessment study with the analysis of the external and internal environment. The study of the external environment should cover economic, political and legal, social and cultural, technological, ecological and other factors that can have either a positive or negative impact on a company's performance. Generally, the external factors related to economic, social and legal environment can be presented as shown in Fig. 7. Moreover, there is other part of factors that covers environmental and climatic issues and, possibly, is the narrowest part of external factors. Yet, as mentions Kiseleva (2019) it includes such issues as the availability of resources, climate conditions, state of nature.

Economic	Social	Legal
<ul style="list-style-type: none"> • Purchasing power • Solvency of counterparties • Credit and tax policy • Level of inflation or deflation • Changing consumer market preferences • Financial and economic crises in other countries 	<ul style="list-style-type: none"> • Unstable political situation • International competition • Consumer's and entrepreneur's culture • Demographic situation 	<ul style="list-style-type: none"> • Unstable legal system • High taxes and their changes • Accounting methodologies and reporting forms • Foreign capital participation

Fig. 7. External factors influencing company's solvency (designed based on Mackevicius, 2018; Kiseleva, 2019)

According to Kiseleva (2019), these indicators are unified, but they all rely on the same criterion – the level of expertise and responsibility of state authorities, as well as their ability to rationally manage the economy of the entire country or individual regions.

The author Dzikevicius (2015) also states that using an integrated enterprise insolvency prediction methodology, it is enough to calculate ten financial ratios indicators. After completing the last step of the methodology – calculating insolvency probability using bankruptcy prediction models a fair and accurate assessment of the condition of the enterprise is gotten in a result. However, the analysis of applied bankruptcy prediction models, applied during step four, is too narrow in Dzikevicius (2015) work as the background was taken only Z.Altman's bankruptcy prediction model. There is no information about the possibility to use other bankruptcy prediction models.

Yet, the internal environment is no less important than the external one, the study of the internal environment should consist of the organizational, management performance, personnel management policy, financial analysis of accounting, internal control and internal audit status evaluation. Kiseleva (2019) points out three main groups of internal factors:

1. Material and technical, these issues are linked with the development of technologies;
2. Organizational – factors that are defined by the management and cover the form of incorporations, choice of products, etc.;
3. Socio-economic, these factors are mostly linked with the employees of a company and their level of competence, as well as working conditions.

Al-Kassar (2014) suggests using certain indicators for an internal environment assessment, the main groups of these indicators are shown in Fig. 8.

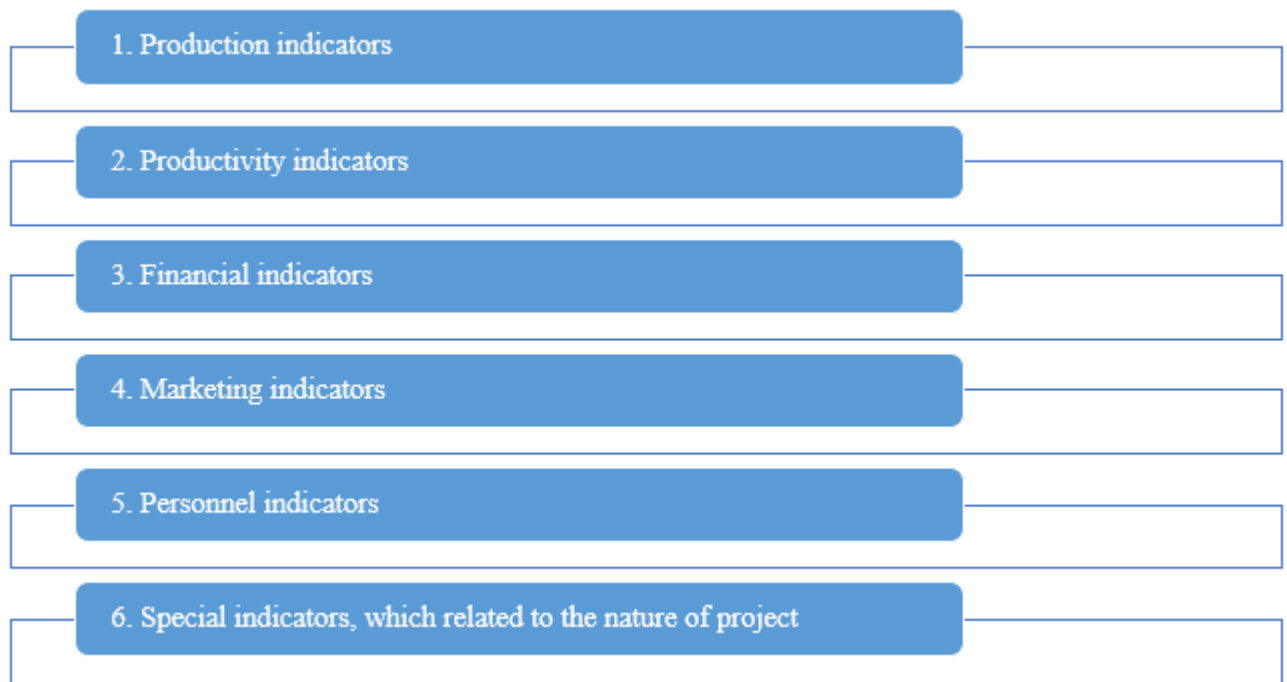


Fig. 8. Indicators, used for internal environment analysis (Designed according to Al-Kassar, 2014)

All indicators, specified in Fig. 8 can be used to fully evaluate company's internal environment by departments. Such indicators could also help to identify if a company faces with a lack of managerial competence. Bruksaitiene (2011) explains that the inability to adjust the company to internal or external requirements, insufficient strategic management, a lack of competence in marketing and operational management, a lack of awareness and skills in accounting and finance, and a lack of control over activities and costs all contribute to a lack of managerial competence. On the other hand, another fundamental factor associated with the company's failure could be a lack of motivation and dedication to the company, indicating a lack of harmonization between the manager's private interests and the company's interests.

Thus, the external and internal factors should be evaluated together to identify the main issues that company could face. There are no more or less important factors, as companies are operating in a complex environment and some factors are highly linked, moreover, market participants are in constant collaboration and enter into various contacts.

The full roadmap (Fig. 9) of company's failure process was created by Bruksaitiene (2011) by observing four types of the company failure: fundamentals of failure, detecting failure, exit of failing company and bankruptcy or recovery. There are substantial discrepancies between these four types of company failure processes in terms of the existence and importance of specific reasons of bankruptcy, namely incorrect management steps, incorrect company's policy steps, and the significance of external factors.

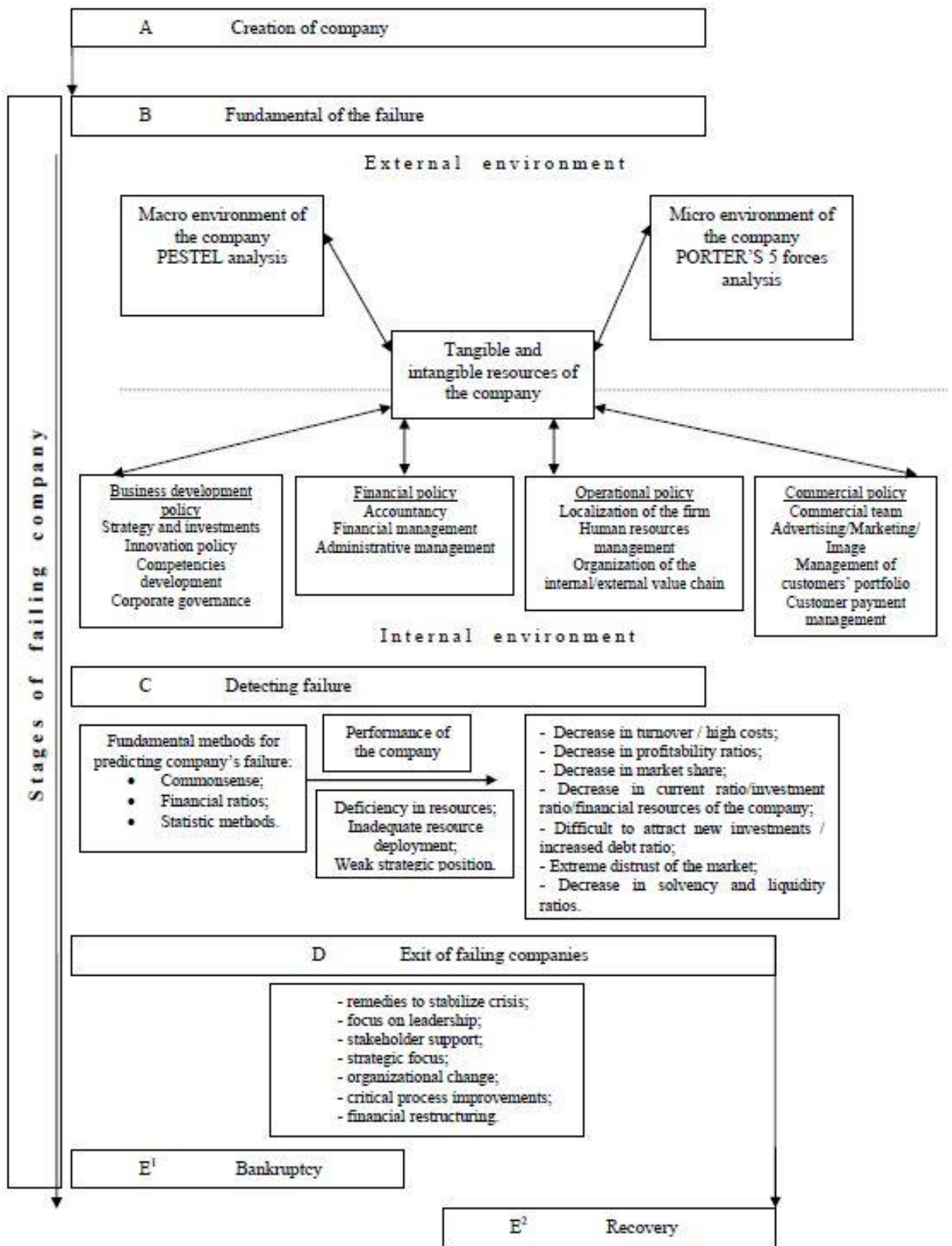


Fig. 9. Company failure process (Bruksaitiene, Mazintiene, 2011)

According to Bruksaitiene, Mazintiene (2011) the first stage is fundamental of failure, at that stage companies often face the lack of resources and cannot create a strategic position on the market. Moreover, at this stage companies usually face with insufficient managerial competencies and an inability to respond to the micro and macro environment requirements. When the company's situation begins to deteriorate, the second stage of failure begins. At this point, three basic methods for predicting a company's failure can be used: common sense, financial indicators, and statistical methods. The common-sense method was firstly introduced by Platt D.H. in 1999. Because this technique employs a subjective measure, the company may survive or even thrive even if all thirteen signs are visible. Hence, the common-sense indicators do not necessarily mean that company will become bankrupt but still, they should be considered. The common-sense failure detectors can be divided into two main groups: company and product. The list of detectors is shown in Fig. 10.

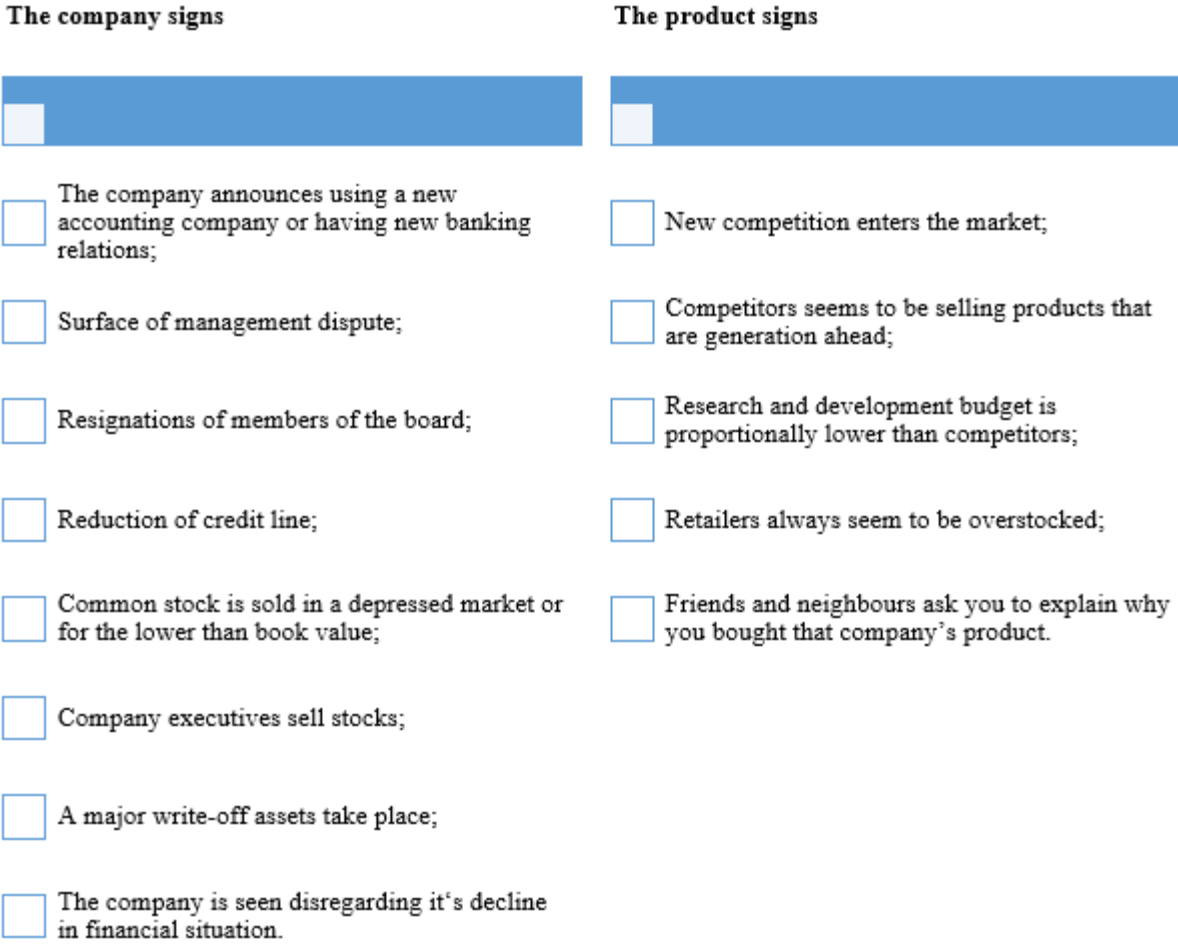


Fig. 10. Common-sense failure detectors (Bruksaitiene, 2011 based on Platt, 1999)

At the second stage of predicting company's failure financial ratios analysis and statistical methods can be used. The financial ratios are easy to calculate, these ratios are also used in several empirical studies. The statistical methods are applied to bankruptcy if the goal is to find indicators that can constantly correctly predict an impending failure. "With increasing number of insolvent enterprises, more and more attention is being paid to the selection of financial analysis methods, assessment of enterprise financial

state and insolvency management so that enterprise management creditors and potential investors could make operational decisions in due time and prevent loss of funds” (Didenko, 2012). The companies that are not publicly listed usually face a higher risk of insolvency due to this they require more attention.

During the third stage of a company's failure detection process, management can take corrective actions to recover. The final stage determines whether the company will go bankrupt or recover. It is obvious that company failure is not a one-time event, but rather a dynamic phenomenon that can be seen in the deterioration of key elements specified in the third stage of the failure process.

Finalizing all the information above, insolvency assessment methodologies could help to address issues in several ways. Efficient insolvency assessment methodologies help to mitigate the negative effects of high private debt on economic activity by freeing up resources trapped in inefficient activities. As insolvency is closely related to bankruptcy it is worth to analyze some of commonly used methods for bankruptcy prediction. The main bankruptcy models mentioned by authors (Grosu, 2019; Feng, 2019; Li, 2019) are Altman’s Z-score bankruptcy prediction model, numerical bankruptcy predictors and hybrid model with static weights. Moreover, the additional financial risk assessment could be made in addition to insolvency risk assessment. Financial risk assessment is mainly based on indexes and indicators calculations. As state Armeanu, 2015; Dang-Ping, 2018 principal components and qualitative and quantitative indexes can be calculated. Deeper research is needed on all the main topics discussed above. Some of the models can become irrelevant in accordance with the research topic, some of them could be only partially applicable.

2.2. Financial ratios used for corporate insolvency assessment

2.2.1. Solvency ratios

“The term solvency generally refers to the capacity of the business to meet its short-term and long-term obligations” (Moorthi, 2012). The other author Ježovita (2015) defines solvency as “the ability of the company to settle all liabilities by available cash, i.e. situation in which a company’s assets exceeds total debt”. Creditors, bank loans, and bills payable are examples of short-term obligations. Debentures, long-term loans, and long-term creditors are examples of long-term obligations. Some authors (Ibendahl, 2016; Ajmal, 2018) suggest using solvency ratios analysis to identify the capability of a unit to meet its long-term obligations. These ratios aid in assessing the risk associated with the use of debt capital. When assessing the state of solvency of a company, the number of debts is firstly considered and the performance of the company, which is characterized by financial indicators, is analyzed. It is not expedient to analyze the level of debts alone, because the company with high debts, but properly fulfilling its financial obligations to creditors is not in a group of risk.

Solvency ratios and liquidity ratios are frequently confused because both are applied to evaluate a company's financial health; however, they are not synonymous. Solvency ratios evaluate a company's long-term health by examining long-term debt and interest on that debt; liquidity ratios assess a company's ability to meet current obligations and convert assets into cash quickly. The difference among solvency and liquidity ratios is presented in Fig. 11.

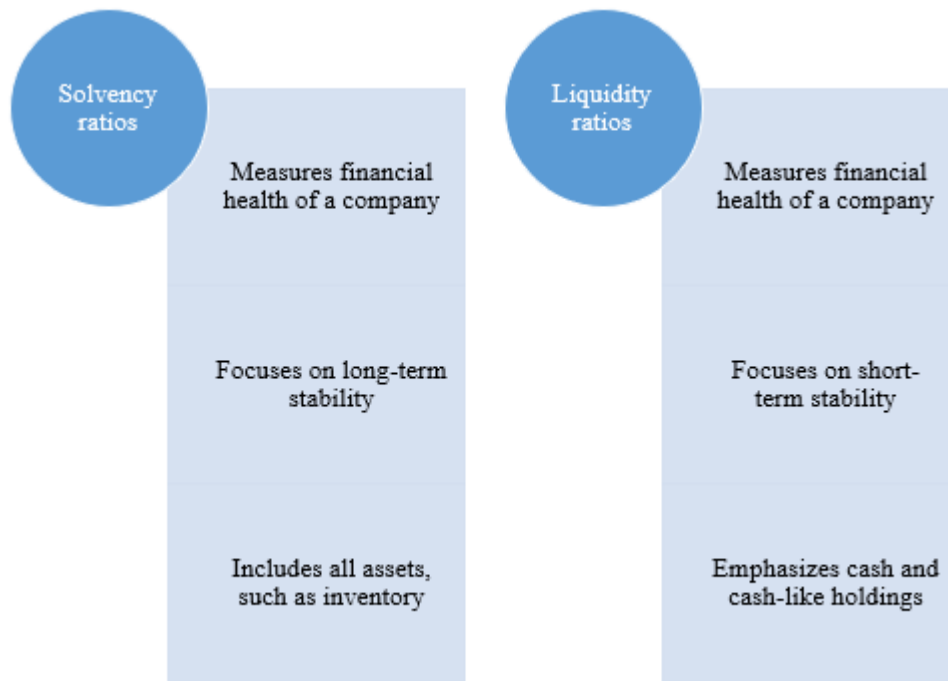


Fig. 11. Solvency and liquidity ratios difference (designed by author)

Solvency ratios can assist business owners and management in identifying downtrends that may indicate the possibility of insolvency in the future. They also aid in determining the proportion between company's debt and its assets and earnings. The main solvency ratios are presented in Table 2.

Table 2. Solvency ratios (designed according to Jezovita, 2015; Ajmal, 2018)

Ratio	Formula	Meaning
The debt-to-assets ratio	Debt ratio = Total liabilities / Total assets	Indicates the proportion of assets that are financed with debt (both short-term and long-term debt).
The equity ratio	Equity ratio = Total equity / Total assets	Shows how effectively a company funds its assets with shareholder equity, as opposed to debt. The higher the ratio, the less debt is needed to fund asset acquisition.
The debt-to-equity ratio	Debt-to-equity ratio = Total liabilities / Total equity	Ratio compares a company's total liabilities to its shareholder equity and can be used to evaluate how much leverage a company is using.

It is worth noting that, as Zelgalve (2015) points out, in the Baltic countries, equity may be negative due to accumulated losses, which is the case for many small and medium-sized businesses in Latvia and other Baltic countries, so the use of the debt-to-equity ratio is limited in some countries because its value will not be objective.

There is one more specific ratio, which can be used as a quick tool for a financial health check and as a ratio to measure a firm’s ability to remain solvent in long term. Brindescu-Olariu (2016) suggests using solvency ratio, which is calculated as follows:

$$\text{Solvency ratio} = \frac{\text{Total assets}}{\text{Total liabilities}} \times 100\% \tag{1}$$

As it can be seen that the formula is very similar to the debt ratio formula, except for the fact that variables are changed in place.

When one of the ratios indicates limited solvency, managers should be alerted. If some of these ratios show the solvency problems, there could be a major issue, especially if the overall economic climate is positive. If a company has solvency problems when the economy is doing well, it is unlikely that the company will fare well during an economic downturn.

2.2.2. Liquidity ratios

Short-term solvency ratios are another name for liquidity ratios. According to Ali (2018), the term liquidity refers to the extent to which assets can be quickly converted into money in order to pay short-term obligations. According to Costea (2009), liquidity analysis focuses on the measure by which companies can meet their obligations with an eligibility term of less than a year, current debts that must be covered by assets with a similar liquidity transformation term. Liquidity ratios are commonly used to decide whether or not to extend credit to a company based on its riskiness. There are three main types of liquidity ratios, which are shown in Fig. 12.

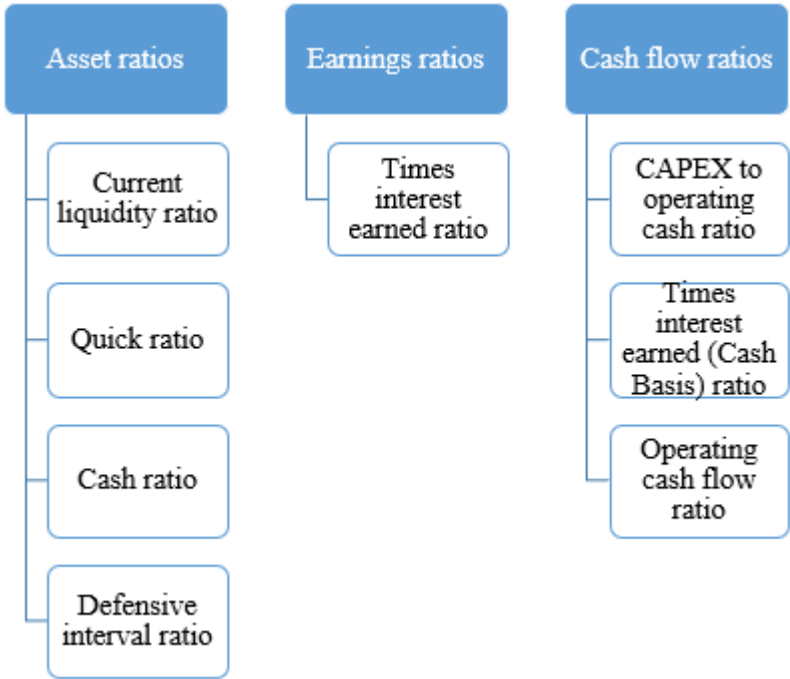


Fig. 12. Liquidity ratios classification (designed by author)

Asset ratios evaluate a company’s liquidity, using the balance sheet assets data, these ratios generally use stricter options of current assets to determine the company’s level of solvency. For calculation of earnings ratios company’s earnings are used. To evaluate a company’s liquidity different kinds of earnings (e.g.

EBIT, EBITDA) can be used, depending on the need of a person who prepares the valuation. Cash flow ratios determine company's liquidity, utilizing cash flow. By using cash flows, it can be determined how well a company's day-to-day operations cover debt obligations. Table 3 shows the most used liquidity ratios during financial analysis.

Table 3. Liquidity ratios (designed according to Costea, 2009; Affandi, 2018; Atieh, 2014; Durrah, 2016)

Ratio	Formula	Meaning
The current liquidity ratio	Current ratio = Current assets / Current liabilities	The current ratio, also known as the working capital ratio, measures the capability of a business to meet its short-term obligations that are due within a year. The ratio considers the weight of the total current assets versus the total current liabilities. It indicates the financial health of a company and how it can maximize the liquidity of its current assets to settle debt and payables. The ideal current ratio is 2:1, however, the current liquidity is considered satisfactory for values between 1.2 and 1.9.
The quick liquidity (acid test) ratio	Quick ratio = Current assets – Inventories / Current liabilities	The quick liquidity ratio, also known as the acid-test ratio, is a liquidity ratio that measures how sufficient a company's short-term assets are to cover its current liabilities. In other words, the quick ratio is a measure of how well a company can satisfy its short-term (current) financial obligations. The quick liquidity is satisfactory for values that are between 0.65 and 1.
The cash ratio	Cash ratio = Cash and Cash equivalents / Current Liabilities	The cash ratio, sometimes referred to as the cash asset ratio, is a liquidity metric that indicates a company's capacity to pay off short-term debt obligations with its cash and cash equivalents. Compared to other liquidity ratios such as the current ratio and quick ratio, the cash ratio is a stricter, more conservative measure because only cash and cash equivalents – a company's most liquid assets – are used in the calculation. The cash ratio indicates the immediate liquidity of the firms. If the cash ratio for the company is too low. This indicates that this company is having immediate problem with paying bills.
The operating cash flow ratio	Operating cash flow ratio = Operating cash flow / Current liabilities	The Operating Cash Flow Ratio, a liquidity ratio, is a measure of how well a company can pay off its current liabilities with the cash flow generated from core business operations. If the ratio is <1, the amount of cash generated from operations is inadequate to fulfill short-term liabilities.

The liquidity of the company consists of cash, cash equivalents and short-term investments and is important to the activity of the company because, in the age of market economy, the most valuable and visible side for each company is its ability to pay – possibility to meet the obligations just in time. A company is considered to be out of cash when it is not able to pay its debts in time. The lack of cash may have immediate consequences: the inability to perform purchases, company’s image destruction due to payment delays – all these consequences result in costs difficult to be accurately assessed. Durrah (2016) highlights the importance of liquidity management as a tool for the management of organizations motivating that liquidity ratios demonstrate an entity's ability to meet short-term liabilities and accenting that inability of valuating these ratios can possibly signify that the company could face complications in settling short-term financial obligations.

Summarising, there are three main types of liquidity ratios, each of the liquidity ratios shows the proportion between a certain type of assets with current liabilities, or, in other words, which part of current liabilities can be covered with a certain type of current assets.

2.2.3. Leverage ratios

Leverage financial ratios are another important block of financial ratios that can be used to forecast future insolvency. Any financial ratio that compares the amount of debt incurred by a company to other accounts on its balance sheet, income statement, or cash flow statement is referred to as a leverage ratio. There are two main types of leverage:

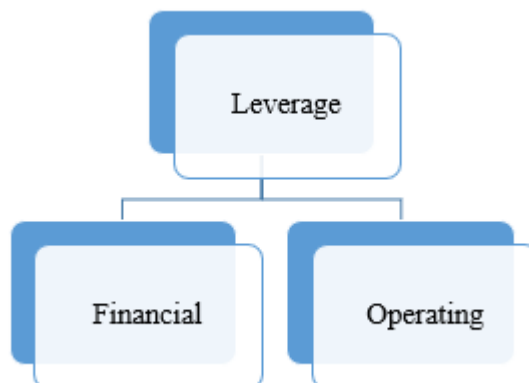


Fig. 13. Types of leverage (designed by author)

The amount to which fixed assets and associated fixed costs are used in the business is referred to as operating leverage. The amount of obligation or debt that a company has used or will use to finance its business operations is referred to as financial leverage.

It is known from the accounting theory, that a company's assets can be financed with either equity or debt. According to Rahmawati (2020), leverage is used to determine how much a company is financed by debt. Excessive debt will jeopardize the company because it will fall into the category of extreme leverage, i.e. the company will be trapped in a high debt level and will find it difficult to get out of debt. Debt financing carries some risk because it obligates the company to pay interest and repay debt as agreed. Except for dividends, which are paid at the discretion of the board of directors, equity financing does not obligate the company to pay anything.

Table 4. Leverage ratios (designed according to Ibendahl, 2016; Moorthi, 2018; Ježovita, 2015; Abrar, 2017)

Ratio	Formula	Meaning
The interest coverage ratio	Interest coverage ratio = Operating income / Interest expenses	Interest coverage ratio can be considered as one of the most important indebtedness ratios. Interest coverage ratio indicates the number of times a firm's income or cash flows could cover interest charges.
The debt service coverage ratio	Debt service coverage ratio = Operating income / Total debt service	The debt service coverage ratio compares a business's level of cash flow to its debt obligations. A ratio value greater than one indicates that the business has enough income to comfortably cover loan principal and interest payments.
Debt-to-EBITDA ratio	Debt-to-EBITDA ratio = Total debt / EBITDA	The debt-to-EBITDA ratio measures the amount of income generated and available to pay debt before covering interest, taxes, depreciation, and amortization expenses.

The other leverage financial ratios can be used by companies to evaluate current debt and debt cost levels, also can convey how dependent a company is on debt funding.

2.2.4. Profitability ratios

For detection of a possible company's failure not only solvency and liquidity ratios can be used, the other important component in assessing company's performance remains profitability. "Profitability is one of the vital elements for performance evaluation, showing the proportion of profit in comparison with asset investment, equity, or sales" (Thi, 2020). The research on a relationship between liquidity and profitability ratios conducted by Adjirackor (2017) demonstrated that there is strong positive relationship between return on asset (ROA) and quick ratio, as well as a strong negative relationship between debt-to-equity and return on assets ratios. To have a full vision of company's performance during the assessment of the risk of insolvency, the analysis of profitability ratios is required. Generally, the profitability ratios are divided into three main groups:

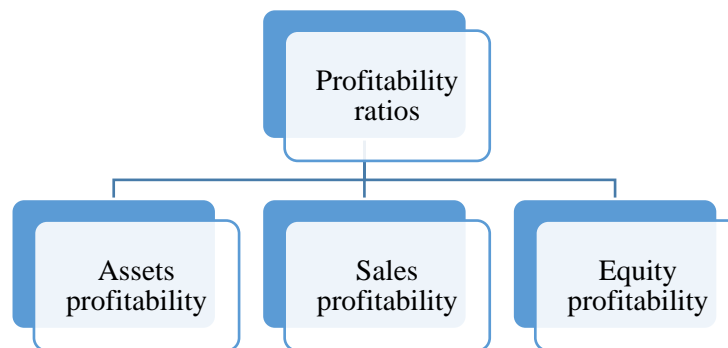


Fig. 14. Types of profitability ratios (designed by author)

The researchers reveal a different number of profitability ratios belonging to each group, usually the group of sales and equity profitability ratios are indicated as the widest with 3-6 different ratios. The least common group of indicators is return on investment with only 1 ratio and this group is not assigned

separately but combined with other ratios. It should also be noted that the profitability of investments can be assessed through other profitability indicators, often - the return on capital group indicators. The level of research of the group of assets profitability indicators varies in the works of different authors, in one's opinion, only 1 indicator of this group is sufficient, others distinguish 3, but often in scientific literature only 2 indicators are assigned to this group. The mostly used profitability ratios are indicated in Table 5.

Table 5. Profitability ratios (designed according to Durrah, 2016; Pandey, 2017; Fathima, 2020; Svabova, 2020)

Ratio	Formula	Meaning
Net profit ratio	$\text{Net profit ratio} = \text{Net profit} / \text{Sales}$	It establishes a relationship between net profit earned and revenue generated from operations.
EBIT margin	$\text{EBIT margin} = \text{EBIT} / \text{Sales}$	It reflects the company's ability to generate profit from ordinary operations related to a company. The decline in this ratio refers to a weak control over operating costs.
Return on assets (ROA)	$\text{ROA} = \text{Net profit} / \text{Total assets}$	It refers to a relationship between net profit and assets. The rise in the ratio refers to an effectiveness of the employment of assets by the company.
Return on equity (ROE)	$\text{ROE} = \text{Net profit} / \text{Equity}$	Ratio measures company's ability to generate profits for shareholders, the value of ROE > 12% accepted as good.

More profitability ratios can be found during the scientific literature analysis, however, some of them are not assigned to a certain group of ratios or are very specific and used for determining the value of a company.

2.3. Classification of bankruptcy prediction models

As explains Rugenyte (2010) the search for indicator or the system of indicators, which could represent the likelihood of corporate bankruptcy has begun back in the 20th century in foreign scientific literature and is still developing. Lithuanian researchers according to Marcinkevicius (2014) have mostly used E.I. Altman's model to analyze and apply bankruptcy prediction models. Though, they have not reached an agreement on how to implement this model for Lithuanian companies. The other author Smaranda (2014) states, that based on the literature review, most failure prediction studies and financial institutions use multiple discriminant analysis or logistic regression, also the author Smaranda (2014) explains this by the ease of the possibility to describe the results using these methods.

A deep research was held in 2006 by Aziz and Dar, when bankruptcy prediction models were classified into 3 main groups – statistical, artificially intelligent expert system models and theoretical models. Fig. 15 shows which types of models belong to each group. Originally, statistical models concentrate on signs of failure and are derived primarily from company accounts, as well as follow the classical standard modelling procedures. These models could be univariate or multivariate in nature. As mentions Aziz (2006) the artificially intelligent expert system models are remarkably similar to statistical as they are also focusing on signs of the failure and derived primarily from company accounts, however, the difference is that these models are usually multivariate in nature. However, this category of bankruptcy prediction models heavily depends on computer technology as it itself is a result of technological

advancement and informational development. The theoretical models are the final type of bankruptcy prediction model. These models typically concentrate on qualitative reasons of failure and are derived primarily from evidence that could appease the theory's theoretical argument of company's failure. These models are multivariate in nature and typically use a statistical technique to give the quantitative support for the theoretical argument.

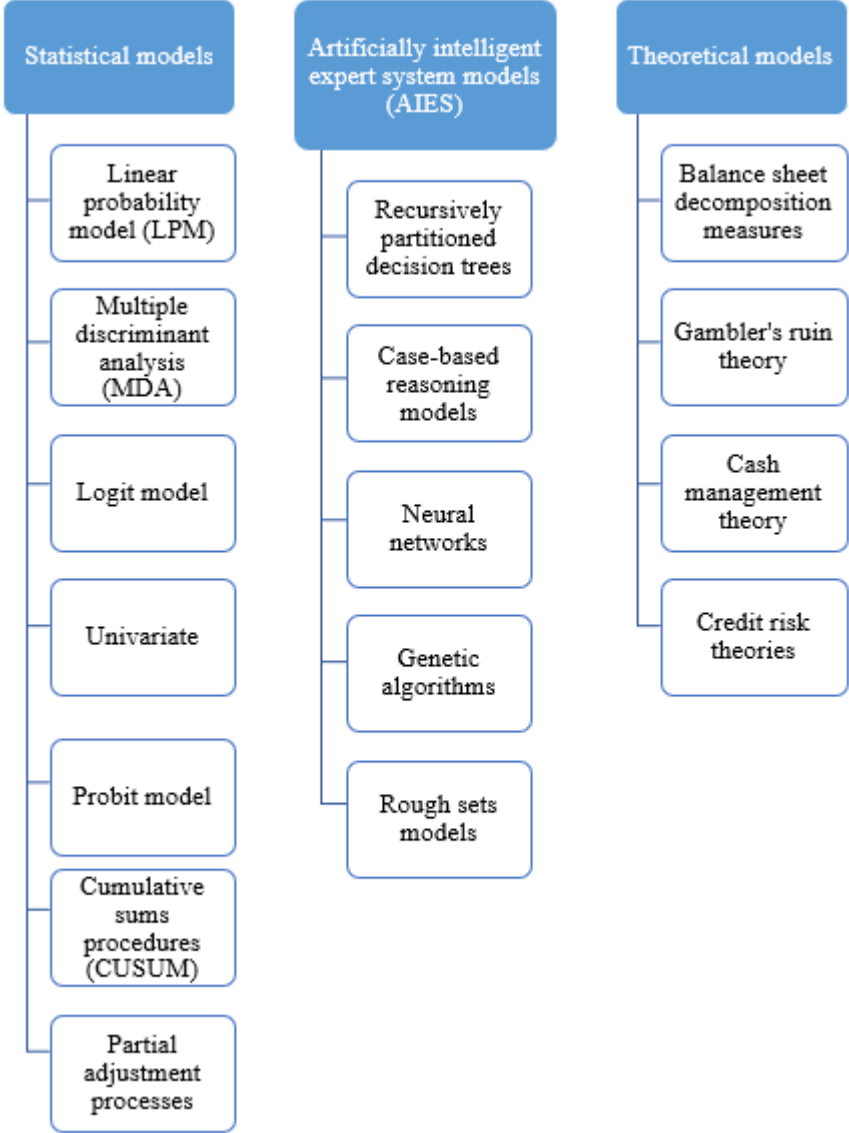


Fig. 15. Bankruptcy prediction models classification (designed according to Aziz, 2006)

Multiple discriminant analysis underpins the most well-known statistical bankruptcy prediction models, as describes Alaka (2018) to categorise companies into one of two groups, a linear combination of variables, typically financial ratios, is used to distinguish between failing and remaining companies. The discriminant coefficients are computed by MDA. A Z-score is calculated using this function. The sample companies' status is used to determine a cut-off Z score. Such models typically have a high level of predictive power.

The other group of popular statistical bankruptcy prediction models are logit and probit models (models of conditional probability), which, based on a cumulative probability function and using a company's financial ratios, calculates the likelihood of belonging to a predetermined group. Logit models are like probit models. Their primary distinction is in the probability function of bankruptcy. (Moharrampour, 2014)

The simplest and easiest to apply are univariate models, which were firstly introduced by Beaver in 1966. As clarifies Appiah (2015) if a firm's value for a ratio is higher than a certain cut-off point, this signals strong financial health and vice versa. However, such models have certain limitations, the most important is that the model neglects multi-dimensional nature of failure.

The most powerful instrument from the group of statistical bankruptcy prediction models are cumulative sums procedures, which were described by Aziz (2006) as a perfect tool for detecting a change in a distribution from one state to another. A finite order VAR model is used to estimate the behaviour of the time series of the attribute variables for each failed and non-failed firm in the case of bankruptcy prediction. The procedure then optimally determines the shift's starting point and provides a signal about the firm's deteriorating state as soon as possible after that. A cumulative (dynamic) time-series performance score is used to evaluate the firm's overall performance at any given point in time (a CUSUM score). If a company's time-series performance scores are positive and greater than a certain sensitivity parameter, the CUSUM score is set to zero, indicating that the firm's financial condition has not changed. A negative score indicates that the firm's condition has deteriorated.

As describes Jaffari (2017) artificially Intelligent Expert System (AIES) models are typically multivariate in nature and information is derived from company's financial statements. These are the result of informational development and technological advancements and they are heavily reliant on computer technology. These models concentrate on symptoms of failure. A decision tree models are frequently used in machine learning, data analysis and statistics. Hung (2009) adds that a decision tree models divide a set of input samples into smaller sets based on some characteristics of their features. In order to group similar samples in the same leaf nodes, a decision tree stores some classification rules in branch nodes.

Case-based reasoning models, as mentioned by Alaka (2018), differ fundamentally from other tools in that they do not attempt to recognize patterns, but rather classify a company based on a sample company with similar attribute values. It justifies its decision by presenting the used sample cases (companies) from its case library and inducing classification decision rules.

According to Moharrampour (2014) the goal of a neural network model is to identify a group of computing elements (neurons) that are related to one another. The computational structure is made up of three layers of neurons: the input layer, the hidden layer, and the output layer.

The same author Moharrampour (2014) explains that the transmission of hereditary characteristics through genes is the central concept of genetic algorithm models. The genetic algorithm is a probabilistic search method that mimics natural biological evolution. Genetic algorithms use the survival of the fittest principle to generate better estimates of an answer from a population of potential solutions. Jaffari (2017) adds that genetic algorithms are a subset of the larger class of evolutionary algorithms that solve

optimization problems using techniques evolved through natural selection. In genetic algorithms, solutions are represented as binary strings of 0 and 1. Other encodings, however, are also possible.

Alaka (2018) explains rough sets models as a theory that assumes there is some information general to all of the objects (companies) in a given universe; information that is given by some attributes (variables) that can describe the objects. Objects with the same attributes are indistinguishable (similar) in terms of the chosen attributes. Rough set creates a universe partition that divides objects with similar attributes into blocks (e.g., failing and non-failing blocks) known as elementary sets. Crossing the boundary line objects cannot be classified because their information is ambiguous. A rough set is used to extract decision rules to solve classification problems.

Balance sheet decomposition model was firstly introduced by Lev (1973). As explains Appiah (2015) this model investigates alterations in the structure of a balance sheet. Significant changes in the asset and liability composition indicate that a firm is unable to maintain its equilibrium state. The main limitation of a model is that it assumes firms try to maintain financial structure equilibrium.

As describes Lim (2012) gambler's ruin theory is based on the assumption that the company's financial state can be defined at any time as its adjusted cash position or net liquidation. The time of bankruptcy is determined by the inflows and outflows of liquid resources, which corresponds to the gambler's ruin model. The value of equity is a reserve, and cash flows either add to or deplete it. In the event of a bankruptcy, the reserve is depleted. The model is based on a well-known statistical problem and intuitively captures a company's default scenario.

Cash management theory focuses on cash management as one of the most important functions of the company. As states Jaffari (2017) companies prepare their cash flow statement in order to manage the short-term cash. When cash inflows exceed cash outflows, such as debtor realization and cash sales, there is sometimes a positive difference; when cash outflows exceed cash inflows, such as tax payments and dividends, there is sometimes a negative difference. If there is a negative difference between cash inflows and cash outflows, and if this difference persists, there is a risk of financial distress, which could lead to bankruptcy.

The last one theoretical model is credit risk theory, which is based on Basel I and Basel II frameworks. Following the guidelines in Basel II, subsequent internal assessment models, such as McKinsey's Credit Portfolio View, JP Morgan Credit Metrics, CSFP's Credit Risk+, and Moody's KMV model, have been developed, according to Aziz (2006). Credit Risk Theories are the names given to these models. The models are founded on microeconomic and macroeconomic concepts of business finance. Corresponding to this theory, a deteriorating economy will attract more downgrades, resulting in an increase in defaults.

The author Kubenka (2016) suggests historical overview of bankruptcy models creation (Appendix 1) specifying the type of a model and its author. The most well-known and used models belong to univariate and multivariate discriminant analysis (MDA) groups. These models usually identified as classic bankruptcy prediction models and have high predictive power. As explains Kubenka (2016) about artificial neural networks models, such models are concentrated on companies based for example on the branch, the size of the company, or the specific business activity. For example, the models focused on the accommodation (hotels/lodging), internet companies agriculture, manufacturing industry, etc.

Kovacova (2017) adds that despite the fact, that artificial intelligence expert systems, including machine-learning techniques, became the primary method for bankruptcy prediction at the beginning of the twenty-first century. While the prediction power of ANNs is relatively higher, there are reasonable limitations such as the need for extensive experience to correctly select the control parameters and difficulties with building the model itself.

According to Barbuta-Misu (2020), the main difficulty with the bankruptcy prediction models developed by the scientists is that they cannot be generalized because they were developed using a specific sample from a specific sector, time period, and region or country. Kristof (2020) adds that even though many appreciated relationships were discovered because of huge model development efforts, no unified agreement has been reached throughout the long history of bankruptcy prediction as to which explanatory variables might best predict corporate failure. The exceptionally broad range of forecasting methods, combined with the various modeling databases from various countries, industries, and time periods, make it exceedingly difficult to speculate on the causes of corporate failure and how to avoid it. The lack of theoretical context for explanatory variables is a significant limitation in developing a general comprehensive theory of bankruptcy prediction. Despite the lack of a widely accepted theory, the conclusion could possibly be that any empirically developed model could be suitable for different economic environment and time period.

2.4. Classic statistical bankruptcy prediction models analysis

2.4.1. Multiple discriminant models analysis

The search for a complex system of ratios suitable for corporate bankruptcy prediction has started in XX century. Historically, the development of bankruptcy prediction models began in the late 1960s, with E. I. Altman developing the first model in 1968. Thus, Altman created the Z-Score model and, with it, the application of multiple discriminant analysis (MDA) in 1968, demonstrating a significant improvement in projection correctness by combining several indicators in one discriminating function. Later, many attempts were made by other researchers who used a strikingly similar methodology. Peres (2017) explains about MDA model, that they assume that the variables of the sample, i.e., the financial indicators to be used, have a normal distribution and, furthermore, that the company under analysis is comparable to the one originally used to estimate the model. Agarwal (2019) clarifies that bankruptcy prediction models have been used to analyze the performance of companies in various industries. Many valuable empirical studies in developed countries have used various models to predict company performance. Gyimah (2018) adds that the “MDA (specifically the Z-score) models seems to be reliable in predicting corporate failure. As well as the use of the Z-score has received international recognition due to its significant predictive power.” However, only a few of the numerous methods available for predicting bankruptcy are well-known and well-established. The most famous and widely used multiple discriminant analysis models are presented in Table 6.

Table 6. Multiple discriminant analysis bankruptcy prediction models (designed according to Budrikiene, 2012; Marcinkevicius, 2014; Kovacova, 2017; Gyimah, 2018; AlAli, 2018; Agarwal, 2019; Verlekar, 2019)

Author, accuracy	Formula	Characteristics of coefficients and their meaning	Bankruptcy probability assessment
Altman (1968), *95%	$Z1 = 1,2X1 + 1,4X2 + 3,3X3 + 0,6X4 + 0,99X5$ $Z2 = 0,717X1 + 0,847X2 + 3,107X3 + 0,42X4 + 0,998X5$ $Z3 = 6,56X1 + 3,26X2 + 6,72X3 + 1,05X4$	X1 – working capital / total assets X2 – retained earnings / total assets X3 – earnings before interest and taxes / total assets X4 – the market value of equity / value of debt X5 – sales / total assets	If $Z1 < 1,81$ – bankrupt; if $1,81 < Z1 < 2,675$ – company in bankruptcy; if $Z1 > 2,875$ – the low likelihood of bankruptcy. If $Z2 < 1,23$ – bankrupt; if $1,23 < Z2 < 2,9$ – company in bankruptcy; if $Z2 > 2,9$ – the low likelihood of bankruptcy. If $Z3 < 1,1$ – bankrupt; if $1,1 < Z3 < 2,6$ – company in bankruptcy; if $Z3 > 2,6$ – the low likelihood of bankruptcy.
Taffler and Tisshaw (1977), *97%	$Z = 0,53X1 + 0,13X2 + 0,18X3 + 0,16X4$	X1 – profit before taxes / current liabilities X2 – current assets / total liabilities X3 – current liabilities / total assets X4 – sales / total assets	If $Z < 0,2$ – bankrupt; if $0,2 < Z < 0,3$ – company in bankruptcy; if $Z > 0,3$ – the low likelihood of bankruptcy.
Lis (1973), *85,5%	$Z = 0,063X1 + 0,092X2 + 0,057X3 + 0,001X4$	X1 – working capital / total assets X2 – gross profit / total assets X3 – retained earnings / total assets X4 – equity / total liabilities	High risk of bankrupt if $Z < 0,037$
Springate (1978), *92,5%	$Z = 1,03X1 + 3,07X2 + 0,66X3 + 0,4X4$	X1 – working capital / total assets X2 – earnings before interest and taxes / total assets X3 – earnings before interest and taxes / current liabilities X4 – sales / total assets	$0,862 < Z$ Good financial health of the company; $Z < 0,862$ Possible financial problems of the company
Fulmer (1984), *98%	$Z = 5,528X1 + 0,212X2 + 0,73X3 + 1,27X4 - 0,12X5 + 2,335X6 + 0,575X7 + 1,083X8 + 0,894X9 - 6,075$	X1 – accumulated profits / total assets X2 – sales / total assets X3 – earnings before interest and taxes / equity X4 – cash / total liabilities X5 – liability / total assets X6 – current liability / total assets X7 – total logarithm of tangible assets X8 – flowing capital / total liabilities X9 – log(EBIT) / interest expense	$Z > 0$ Good financial health of the company; $Z < 0$ Bad financial health of the company

Table 6 continued

Author, accuracy	Formula	Characteristics of coefficients and their meaning	Bankruptcy probability assessment
CA-Score (1987), *83%	$CA - Score = 4.5913 A + 4.5080 B + 0.3936 C - 2.7616$	A - Shareholder's investment / Total assets B - Earnings before taxes and extraordinary items + Financial expenses / Total assets C - Sales / Total assets	$CA - Score < -0.03$; then the firm is called as "failed"
Altman II (2000), *98%	$Z = 0.717X1 + 0.847X2 + 3.107X3 + 0.420X4 + 0.998X5$	X1 - Working Capital / Total Assets X2 - Accumulated Retained earnings / Total Assets X3 - Operating Profit / Total Assets X4 - Equity / Total Liabilities X5 - Sales Revenue/Total Assets	$Z > 2.9$ safe or success firm, $Z < 1.23$ is categorized as failed firms, $1.23 < Z < 2.9$ is the gray area or the ignorance zone
Grover (2001), *100%	$G = 1.650X1 + 3.404X2 - 0.016ROA + 0.057$	X1 - Working capital / Total assets X2 - Earnings before interest and taxes / Total assets ROA - net income / Total assets	$GS \leq -0.02$ = bankrupt $GS \geq 0.01$ = health

*Model prediction accuracy one year before bankruptcy

Each of the bankruptcy prediction models has from 4 up to 9 variables, each of the variables has a certain coefficient. The oldest and the best-known bankruptcy prediction model was designed by E. Altman. According to Freifalts (2018) E. Altman was the first researcher who, using the statistical method, the analysis method of a compound discriminant, developed a bankruptcy prediction model – the Z-function. Later Altman also developed two models for non-listed companies. As explains Grdic (2017) the methodology includes building the solvency profile of a company based on its issued financial accounts. It is worth to mention, that there are a lot of discussions about the adequacy of using Altman Z-score model for predicting insolvency of European business units. Altman's model was revised several times, lastly in 2000, when the general appearance of a formula and its coefficients was changed. It is considered that an accuracy of a revised model has increased.

As describes Kubecova (2014) the Taffler's Model was established in response to Altman model in 1977. The Taffler's Model monitors the company's risk of insolvency. This model is well-known in both its original and modified variations. When less detailed data is available, the modified form is used, and different indicators are used. The final evaluative indicator in the basic formula is the share of financial assets net of current liabilities to operating costs; in the modified version, this indicator is replaced by the sales-to-asset ratio. The main disadvantage of Taffler's Model is that it is used only for top and big enterprises.

Springate model is defined by Fakhti-Husein (2014) as a revolution of the Altman model developed by Multiple Discriminant Analysis (MDA). According to the author, the Springate model development process began with the use of 19 commonly used financial ratios. However, after extensive testing, Springate settled on four financial ratios to be used in determining whether the company is considered healthy or potentially insolvent. The model has a 92.5 percent accuracy rate according to the Springate test. The Springate method can be used to evaluate a company's condition and performance for the parties involved. Furthermore, Springate has been discovered to be a method for predicting the company's future bankruptcy and can be used as an early warning system of bankruptcy.

According to Shalih (2019), the Fulmer's model used the step-wise multiple discriminant analysis method to evaluate 40 financial ratios applied to a sample of 60 companies. According to Fulmer, 30 companies failed while the other 30 succeeded. The Fulmer model has 9 ratios and reports an accuracy rate of 98 percent to the company one year before it fails and an accuracy rate of 81 percent more than one year before bankruptcy. Shalih (2019) adds that the Springate Model and the Fulmer Model are models that can predict company bankruptcy in the future and serve as an early warning for management to reevaluate the company's financial performance when bankruptcy is identified.

According to Rajasekar T. (2014), the CA-Score model was created using stepwise multiple discriminant analysis under the direction of Jean Legault of the University of Quebec in Montreal, Canada. In a sample of 173 Quebec manufacturing firms, the model used thirty financial ratios. The model was found to be most useful in the manufacturing industry.

As explains Verlekar (2019) The Grover model was created by restoring or redesigning the Altman Z-Score model. The model starts with X1 and X3 from the Altman model and then adds profitability ratios such as Return on Asset (ROA). As a result, the Grover model is the best predictive model for companies

in the food and beverage industry. The research shows that the Grover model has the highest level of accuracy that is equal to 100%.

As highlights Krusinskas (2014) models of linear discriminant analysis provide only a linear dependence between financial indicators and the probability of bankruptcy; however, under rapidly changing economic conditions, this dependence is usually not so simple and direct. The multiple discriminant analysis models have a lot in common, they use similar variables, however, each variable has a different weight in a formula. Moreover, this group of bankruptcy prediction models has its own applicability advantages and limitations, which are presented in Fig. 16.

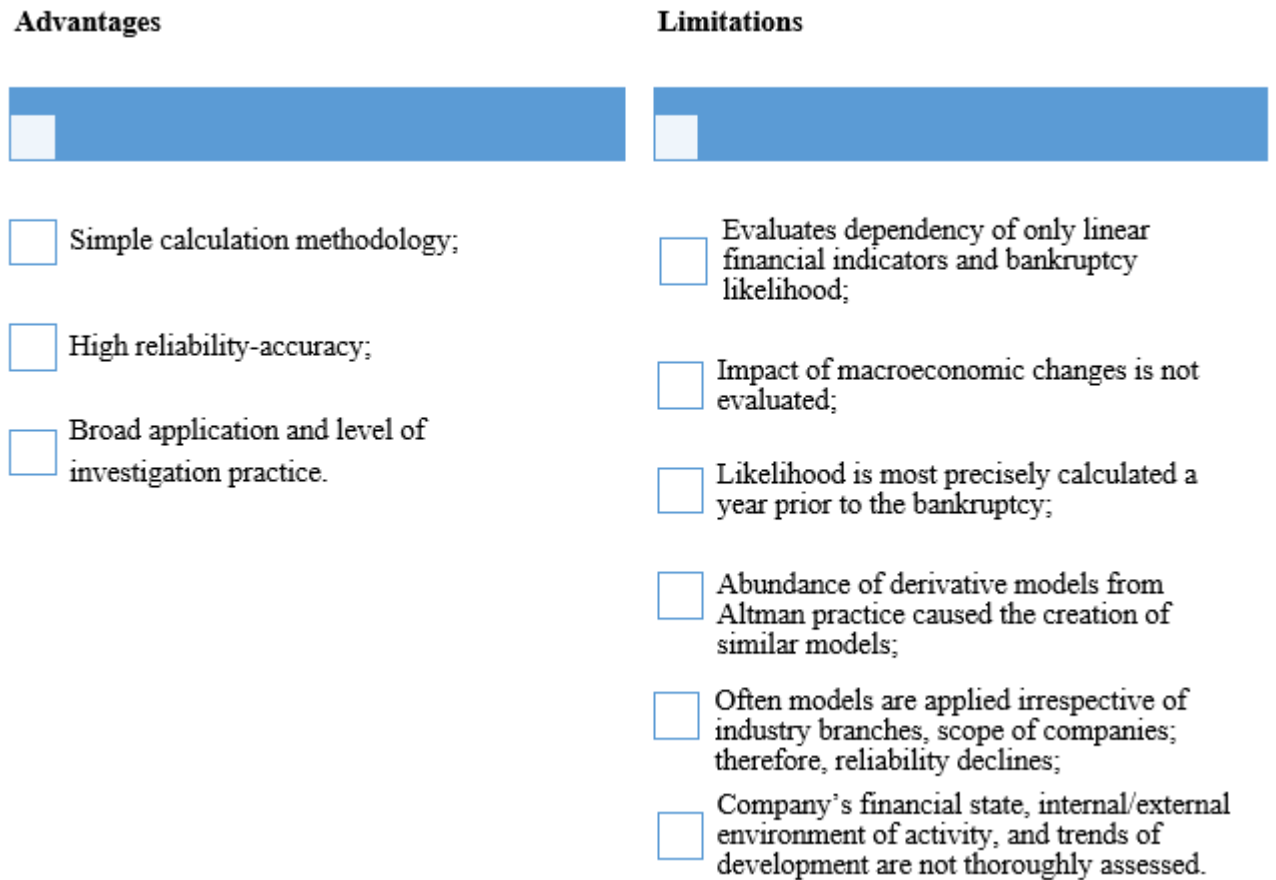


Fig. 16. Advantages and limitations of multiple discriminant analysis models (designed based on Giriuniene, 2019)

As it can be seen, the main advantages of MDA models are their simple calculation methodology and high accuracy, however, these models do not evaluate the impact of macroeconomic changes or company's external and internal environment. Additionally, the high accuracy remains only if the calculations are performed a year before the potential bankruptcy.

2.4.2. Logit and probit models analysis

Since the 1970s, the field's evolution has been driven by the modernization of mathematical-statistical classification methods and the IT solutions that support them. As describes Kristof T. (2020) passing through the distribution and variance assumptions of DA, logistic regression (logit) has become an

increasingly popular bankruptcy prediction method, first used on a credit risk database by Chesser (1974). Ohlson's (1980) publication marked a watershed moment in the global distribution of logit, expressing that insolvent companies account for a smaller proportion of the population than solvent ones. For similar methodological reasons, the use of probit regression (Zmijewski 1984 model) began in the 1980s. Based on a cumulative probability function and a company's financial ratios, these models determine how likely it is for a company to belong to one of the predetermined groups. Because of the limitations of multivariate discriminant analysis methods, studies on commercial insolvency focused primarily on logit models after 1981. Logit models are similar to probit models. The main distinction is in the bankruptcy probability function. In most cases, logit models are preferred over probit models because probit models necessitate more calculations than logit models. This is because nonlinear estimations are used. The most used logit and probit bankruptcy prediction models are provided in Appendix 2.

According to scientific research studies (Kanapickiene R. (2014), the Chesser bankruptcy prediction model has an accuracy of 78 percent one year before bankruptcy filing and 57 percent two years before filing.

As mentioned by Imelda (2017); Rajin (2016) Ohlson model was developed using data from the year 1970 to 1976 of 105 manufacturing companies that went bankrupt and 2058 companies that were not bankrupt during the period. The main difference is that the data was from the financial statements issued for taxes. Ohlson employed the logit statistical method. Ohlson believed the method could compensate for Altman's Multiple Discriminant Analysis flaw. His work was based on determining the probability of bankruptcy for a given company if it fits in to a specific population. As a result, the analysis is conducted without a pre-determined likelihood of bankruptcy and without the likelihood of distribution indicators.

As explains to Jamshedi (2014) Zavgren model was developed by calculating the coefficients of normal bankrupt companies for five years from 1975 till 1979 by financial statements of normal bankrupt companies calculated the coefficients of his model for five years. The bankruptcy probability of a bankrupt company was then calculated using the coefficients, and it was discovered that from 1975 to 1979, the bankruptcy probability of a bankrupt company was increasing. Later, the changes in the bankruptcy probability of the mentioned company were compared to the stock price trend of the company during those years, and it was discovered that while the company's bankruptcy probability was ascending, the stock price was descending, and it was reduced as the bankruptcy probability increased. As in the Zavgren model, the population's normalcy is not taken into account; however, it is close to reality, and the Altman model is applied in most populations with varying conditions based on the assumptions upon which the model is formulated. One of the issues is that the calculated coefficients of the variables in the Zavgren model had low correlation due to the unreliability of the normality assumption, variable distribution and model ratios, and direct use of non-parametric statistics analysis and logit model to find the ratios coefficients and prediction model variables compared to the audit analysis models as Altman model.

According to AlAli (2018), the most commonly used model by accounting researchers is the Zmijewski X-score model, which employs a probit method to model bankruptcy and employs financial ratios to

measure a firm's performance, leverage, and liquidity. For the period 1972–1978, the model used data from 40 bankrupt and 800 non-bankrupt industrial firms. He claimed that the model had a 99 percent accuracy rate in predicting company bankruptcy two years before it occurred. Unlike Altman's Z-model, Zmijewski X-Score does not have any criteria threshold values against which to compare the results.

Sivolapenko (2020) states that The A.Y. Belikov-G.V. Davydova model is comprised of four components. The K1 ratio (Working capital / Assets) is from Altman's model, and the K3 financial ratio (Revenue / Assets) was used in the Taffler bankruptcy model. The remaining financial ratios have never been used before by foreign authors. According to the Belikov-Davydova model, the first financial coefficient (K1) is critical in assessing an enterprise's bankruptcy. This is because it has a specific weight of 8.38, which is significantly greater than the rest of the financial ratios in the model. The model was developed using data from a sample of commercial enterprises that went bankrupt but remained financially stable. Šlefendorfas (2016) states that although the majority of those models are used globally, researchers are still developing new models that are applied to companies operating in a specific country. As well as MDA model, logit and probit models also have certain advantages and limitations in use, which are presented in Fig. 17.

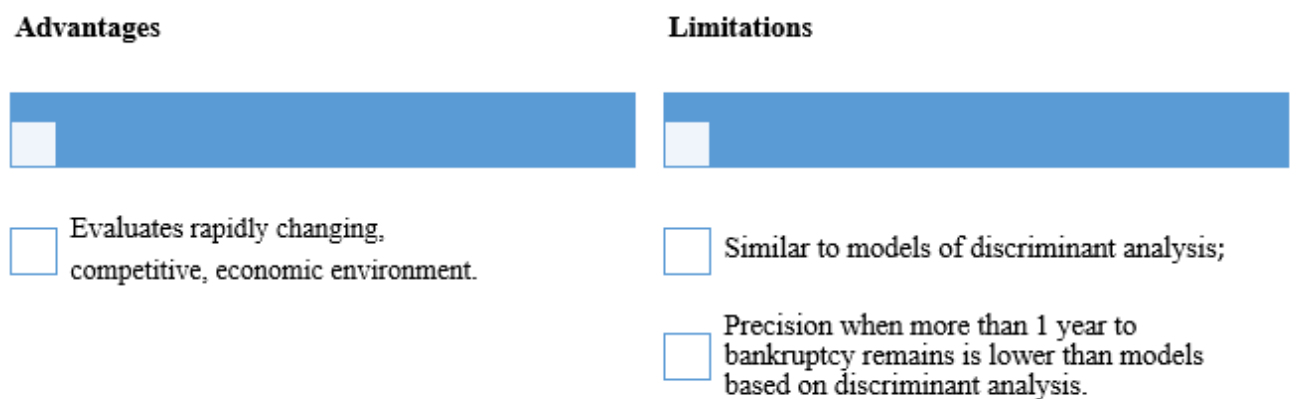


Fig. 17. Advantages and limitations of logit and probit models (designed based on Giriuniene, 2019)

The main difference between MDA and logit (probit) models is that the latter evaluates the rapidly changing competitive environment. However, logit and probit models work the most precisely if a year before possible bankruptcy remains. In this case the similarity between MDA and logit and probit models persists, both types of models work the better, the shorter the prediction period is. Although, the overall accuracy of most logit and probit models is lower than MDA models.

2.5. Kralicek tests for insolvency risk assessment

For insolvency assessment some authors (Didenko, 2012; Polo, 2014; Kubenka, 2016; Grdic, 2017) suggest using Kralicek quick test, which lets determine the financial situation of the unit. As states Grdic (2017) “the Kralicek Quick Test includes both dynamic and static indicators. To reach a conclusion related to financial state of an economic unit using Kralicek Quick Test, it is necessary to have available

some indicators taken from the balance and the statements of income and costs.” This method provides a rapid and accurate assessment of paying incapacity.

As describes Vidimlic (2018) Peter Kralicek has produced two models, based on the financial indicators of Swiss, German and Austrian companies. Firstly, the Quick test was introduced, which, as his name indicates, could, at first look, estimate the company's solvency. Didenko (2012) enhances that Kralicek quick test was developed in 1990 and provides a quick and accurate insolvency assessment. The evaluation is based on the calculation of four factors (two indicators of financial stability and two indicators of efficiency), Machek (2014) adds that Kralicek test is an example of “solvency models” and evaluates the company’s financial and revenue position. It takes into account multiple financial ratios and assigns the following scores according to the resulting values. As mentions Machek (2014) Kralicek quick assesses company’s position from very weak to very good. The position is assessed according to the test results, where each indicator’s values are grouped. The logic of Kralicek quick test indicators is shown in Fig. 18.

Indicator		Points				
		0	1	2	3	4
X_1	Assets / Equity	$X_1 > 0.8$	$0.8 > X_1 > 0.6$	$0.6 > X_1 > 0.4$	$0.4 > X_1 > 0.2$	$0.2 > X_1 > 0$
X_2	(Liabilities + loans) / Operating cash-flow	$X_2 > 0.8$	$0.8 > X_2 > 0.6$	$0.6 > X_2 > 0.4$	$0.4 > X_2 > 0.2$	$0.2 > X_2 > 0$
X_3	EBIT / Assets	$X_3 > 0.8$	$0.8 > X_3 > 0.6$	$0.6 > X_3 > 0.4$	$0.4 > X_3 > 0.2$	$0.2 > X_3 > 0$
X_4	Operating cash-flow / Sales	$X_4 > 0.8$	$0.8 > X_4 > 0.6$	$0.6 > X_4 > 0.4$	$0.4 > X_4 > 0.2$	$0.2 > X_4 > 0$

Note: X denotes the value of the indicator in the row

Fig. 18. Kralicek quick test (Machek, 2014)

Fig. 18. shows that the ranges for all indicators in a certain group are the same. After the calculation of indicators, the total test score is calculated. Corresponding to the score the company’s position is identified.

Score	Position
4	Very good company
3	Good company
2	Average company
1	Weak company
0	Very weak company

Fig.18. Kralicek quick test score (Machek, 2014)

Another model, called the DF indicator, as states Vidimlic (2018) is the revised version of Kralicek quick test, developed in 1999, which includes six financial indicators, different weights, expressed through weights. The method established as a DF indicator looks as follows Grdic (2019):

$$DF = 1.5 X_1 + 0.08 X_2 + 10 X_3 + 5X_4 + 0.3 X_5 + 0.1 X_6 \quad (2)$$

Where:

DF – Kralicek DF indicator

X1 – net cash flow/total liabilities

X2 – total assets/total liabilities

X3 – earnings before interest and taxes (EBIT)/total assets

X4 – earnings before interest and taxes (EBIT)/revenues

X5 – inventories/revenues

X6 – operating revenue/total assets

According to Grdic (2019) the most important indicator is X3, while X2 is the least important. The indicator X1 shows the level to which net cash flow covers the liabilities. X2 shows the share of liabilities in total assets; X3 displays the company's profitability; X4 displays total income profitability; X5 shows how many units of operating income are engaged in reserve funds; and X6 shows how much revenue is generated by a single assets unit. The DF indicator's value can be both negative and positive. A negative value for a function immediately indicates the enterprise's insolvency. Higher values indicate that the company is in a better financial position. Vidimlic S. (2018) suggests using the following DF indicator scoring system:

THE VALUES OF DF INDICATOR	FINANCIAL STABILITY
>3,0	EXCELLENT
>2,2	VERY GOOD
>1.5	GOOD
>1,0	AVERAGE
>0,3	BAD
≤0,3	BEGINNING OF INSOLVENCY
≤0,0	MODERATE INSOLVENCY
≤-1,0	THE STRIKING INSOLVENCY

Fig.20. Kralicek DF indicator scores (Vidimlic, 2018)

As explains Rajin (2016) Kralicek's DF indicator can have both positive and negative values, with the negative indicating the presence of insolvency and the positive indicating the solvency of the monitored business entity. Insolvency begins when the DF indicator's value is between 0.0 and 0.3, after which the area of moderate insolvency begins for DF indicator values between 0.0 and -0.1, after which the area of severe insolvency begins. Financial stability is weak for indicator values greater than 0.3-1.0, and medium for values between 1.0 and 1.5. Stability is good for business subjects with DF values between 1.5 and 2.2, and very good for subjects with DF values greater than 3. All companies with a DF indicator greater than 3 are considered to have exceptional financial stability.

The main advantage of Kralicek DF indicator method that can be identified – a very detailed assessment, in this case companies are grouped not only to failed or healthy, but also the level of financial distress can be detected.

2.6. Summary of the scientific literature analysis results

The analysis of the scientific literature shows that insolvency risk assessment is a complex action that is not limited by the analysis of financial ratios or application of only one model. The techniques used for an insolvency risk assessment depend on the country and sector where the company operates, the ability to obtain the required data for the analysis and even on the personality of an appraiser. Although, there are a lot of factors, influencing company's performance and the main question that still exists is how to assess non-financial factors. Generally, the information analysed can be arranged in a conceptual model provided below:

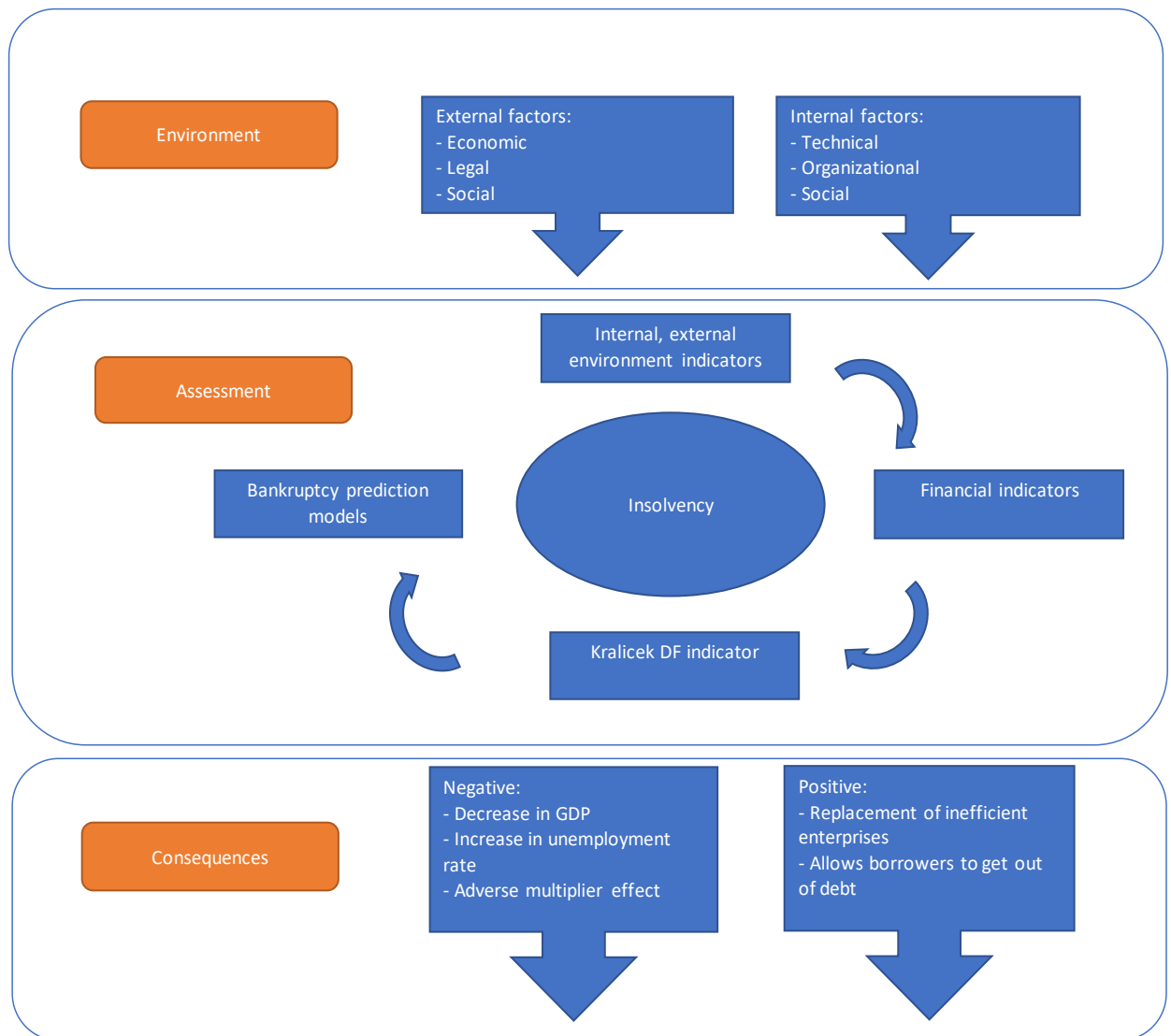


Fig. 21. The conceptual model based on scientific literature analysis (designed by author)

The concept begins with the environment, which includes both external and internal factors that influence the insolvency risk. Furthermore, if a company becomes insolvent as the final stage, the consequences of this incident are also displayed; typically, the consequences are felt primarily for economics and society, as well as for other businesses. The insolvency risk assessment comes in between those two stages. The assessment should begin with the identification of the influencing internal and external factors, followed by the application of other financial techniques, which typically combine the analysis of financial ratios as well as the application of other possible financial risk assessment methods. The main question left after the scientific literature analysis is how to evaluate the external factors and their influence of a company's performance. There is no unified practice that is applicable to all companies in various industries. However, it is still possible to examine the main indicators.

Furthermore, the methodology for an empirical research will be created based on the conceptual model.

3. Insolvency risk assessment of companies listed on the NASDAQ Baltic stock exchange research methodology

As states Barbuta-Misu (2020) assessing insolvency risk is important specifically for investors and managers during the decision making process. After the theoretical aspects of insolvency analysis, it was noticed that the term insolvency can be often confused with the bankruptcy term, however, the research showed that for detailed insolvency risk assessment the usage of bankruptcy prediction models can be helpful. The other important insight relates to the identification of key external factors, that can potentially influence the number of insolvencies.

The main aim of the research is to check which financial indicators and models can be applicable during insolvency risk assessment, to identify the differences of methods and models used during the research, find out any limitations that occurred.

This part of the thesis presents the model of the insolvency risk assessment research and its main stages, as well as the methodology of the empirical research. The research will be conducted in several steps, the steps are presented in Fig. 22.

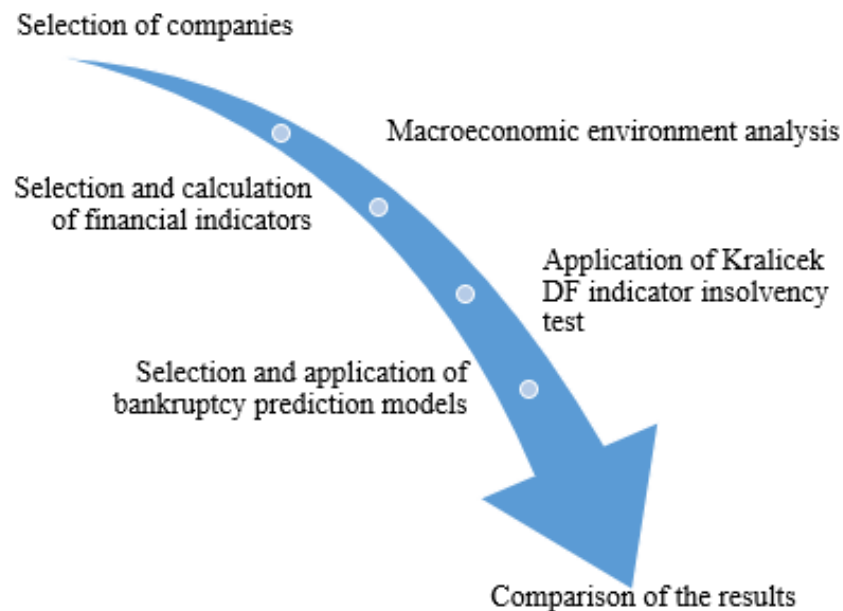


Fig. 22. Flowchart of the research (designed by author)

1 stage: selection of companies

The Baltic States market was chosen for several reasons. Firstly, the Baltic States have a lot of similarities in history, development, and economic conditions. Secondly, the comparison between companies operating in different sectors is easier when the governmental regulation is close enough. Companies were chosen considering the following limitations:

- Excluding companies that operate in financial or investment sectors, due to fact that these companies have a different structure of capital;
- Excluding companies that are listed on the First North list as the regulations for these companies are not applied;
- Excluding companies that are under the process of liquidation, or delisting from the stock exchange;
- Excluding companies with missing values of financial indicators or set of financial statements for the year 2020.

The number of companies by sector and country is provided in Table 7. A detailed list of companies is provided in Appendix 3.

Table 7. Companies number by sector (designed by author)

Sector	Lithuania	Latvia	Estonia	Total by sector
Basic Resources	2			2
Construction and Materials	1		2	3
Consumer Products and Services	3		3	6
Energy	1			1
Food, Beverage and Tobacco	6	2	1	9
Health Care		2		2
Industrial Goods and Services	1		2	3
Media			1	1
Real Estate		1	2	3
Retail	1		1	2
Technology		1		1
Telecommunications	1	1		2
Travel and Leisure			1	1
Utilities	3	1		4
Grand Total	19	8	13	40

2 stage: macroeconomic environment analysis

During this stage, the most important macroeconomic factors are assessed. Examining the business environment, it is essential to determine the impact of the business environmental elements on the number of corporate insolvencies in the country. For analysis, the following economic indicators were chosen:

- Number of insolvent companies
- Gross domestic product (GDP), mil. EUR
- Capita gross domestic product (GDP per capita), EUR
- Inflation rate, %
- Unemployment rate, %
- Import, mil. EUR
- The overall number of companies

In determining the relationship between the factors under consideration methods of correlation analysis are going to be used. For the research, the following correlation coefficient ranges are agreed upon:

Table 8. Correlation coefficient values (designed based on Rather B., 2009)

Range	Meaning
0	no linear relationship
+1	perfect positive linear relationship – as one variable increases in its values, the other variable also increases in its values through an exact linear rule.
-1	perfect negative linear relationship – as one variable increases in its values, the other variable decreases in its values through an exact linear rule.
0 – 0.3 (0 and -0.3)	weak positive (negative) linear relationship through a shaky linear rule.
0.3 – 0.7 (-0.3 and -0.7)	moderate positive (negative) linear relationship through a fuzzy-firm linear rule.
0.7 – 1 (-0.7 and -1)	strong positive (negative) linear relationship through a firm linear rule.

All the values of economic indicators for the 2018-2020 years period are taken from Statistics Lithuania, Statistics Estonia and Official statistics of Latvia databases.

3 stage: selection and calculation of financial indicators

At this stage, the key financial indicators for the company’s solvency, liquidity and profitability assessment will be calculated. The indicators will be calculated for each company for 2018, 2019 and 2020 year. The following indicators were chosen:

Table 9. Selected financial indicators for calculation (designed by author)

Solvency, liquidity	Profitability
Current ratio	Net profit margin
Quick ratio	EBIT profit margin
Operating cash flow ratio	Return on Assets (ROA)
Debt-to-Assets ratio	Return on Equity (ROE)
Debt-to-Equity ratio	

All financial indicators will be calculated using the data from balance sheets, profit and loss statements and statements of cash flow provided on the NASDAQ Baltic stock exchange. After calculation and analysis of financial indicators, all analysed companies will be divided into four groups: solvent and profitable; solvent and unprofitable; insolvent and profitable; insolvent and unprofitable.

4 stage: application of Kralicek DF indicator insolvency test

At this stage, the Kralicek DF indicator insolvency test will be applied for all the companies. Kralicek DF indicator was chosen as a relatively new way for insolvency risk assessment, which had not been used by Lithuanian researchers before. The second reason for choosing this method is its complexity and a detailed insolvency level assessment scale. The main aim of applying the Kralicek DF indicator is to check if it is suitable for companies operating in the Baltic States, to identify if it has any limitations or disadvantages.

5 stage: selection and application of bankruptcy prediction models

As an aid for insolvency risk assessment six bankruptcy prediction models were chosen: 4 MDA models and 2 logit and probit models, the reason for choosing each model is determined in Table 10.

Table 10. The reasoning of the selection of bankruptcy prediction models (designed by author)

Model name	Motivation for application
Taffler and Tisshaw (1977)	High accuracy level, can be used for big enterprises
Springate (1978)	Relatively high accuracy level, suitable for bankruptcy prediction in the future
Zmijewski (1984)	High accuracy level
Altman II (2000)	High accuracy level, suitable for publicly listed companies
Grover (2001)	High accuracy level, barely used in research, was not applied in the Baltic States yet
Grigaravicius (2003)	High accuracy level, developed by Lithuanian researcher

In scientific literature, the application of bankruptcy prediction models is identified as the latest step during the probability of insolvency or financial distress assessment.

6 stage: comparison of the results

At this stage, the results will be compared in two ways. Firstly, a comparison will be made between the results provided by financial ratios analysis and the Kralicek DF indicator. This could help to identify the gap between the results and to check if the Kralicek DF indicator is suitable for companies operating in the Baltic market. Secondly, all applied bankruptcy prediction models are compared in between to identify the differences and to specify which models are suitable as an additional method for an insolvency risk assessment.

4. Insolvency risk assessment of companies listed on the NASDAQ Baltic stock exchange research findings and discussion

4.1. Macroeconomic environment analysis

The macroeconomic environment is supposed to be related to the number of insolvencies in the country. Evidently, companies do not become insolvent only because of the economic conditions in the country, the internal factors influence corporate insolvency as well. Nevertheless, to identify if the corporate insolvencies are influenced by macroenvironmental factors, the correlation analysis will be used. The following abbreviations are used in the calculation:

Y - Number of insolvent companies

X1 - Gross domestic product (GDP), mil. EUR

X2 - Capita gross domestic product (GDP per capita), EUR

X3 - Inflation rate, %

X4 - Unemployment rate, %

X5 - Import, mil. EUR

X6 - Overall number of companies

Appendix 4 presents the dynamics of the number of corporate insolvencies and macroeconomic indicators for the period 2018-2020. The dynamics of the main macroeconomic indicators are shown in Fig. 23. To estimate if there is a connection between the data, the correlation between a dependent variable (number of insolvencies) and independent variables (macroeconomic indicators) will be calculated.

It is noticeable that there is a similar general dynamic across the Baltic States on all the indicators. In the case of the GDP indicator, the general dynamic is the increase of an indicator from 2018 to 2019 and a decrease from 2019 to 2020. The same dynamics applicable to an indicator GDP per capita, it is worth to mention, that in Estonia GDP per capita indicator is the highest among the Baltic States. An inflation rate dynamic varies across the countries, in Lithuania it can be seen a decrease in the inflation rate during the period 2018-2020, in Latvia inflation was growing from 2018 to 2019, however, it lowered in 2020. In Estonia, the inflation rate decreases over 2018-2020. The unemployment rate was growing in Lithuania during all period 2018-2020, in Estonia and Latvia the unemployment rate decreases in 2019 in comparison with 2018, however, it can be seen an increase in 2020. Imports increased in Latvia and Lithuania in 2019 in comparison with 2018, however, decreased in 2020. In Estonia, imports were increasing during 2018-2020. The total number of companies is the highest in Latvia and Estonia, surprisingly in Lithuania, the total number of companies is the lowest among the Baltic States. In Estonia the total number of companies was increasing each year during 2018-2020, in Latvia, however, the was a decrease in 2019 in comparison with 2018 by 1.3.% but in 2020 the total number of companies was even higher than in 2018. For Lithuania a similar trend as for Estonia is applicable, the total number of companies was growing each year in the period 2018-2020.



Fig. 23. The dynamics of the main macroeconomic indicators for 2018-2020

The correlation analysis lets evaluate the strength of the connection between a number of insolvent companies and other factors, its results are presented in Fig. 24.

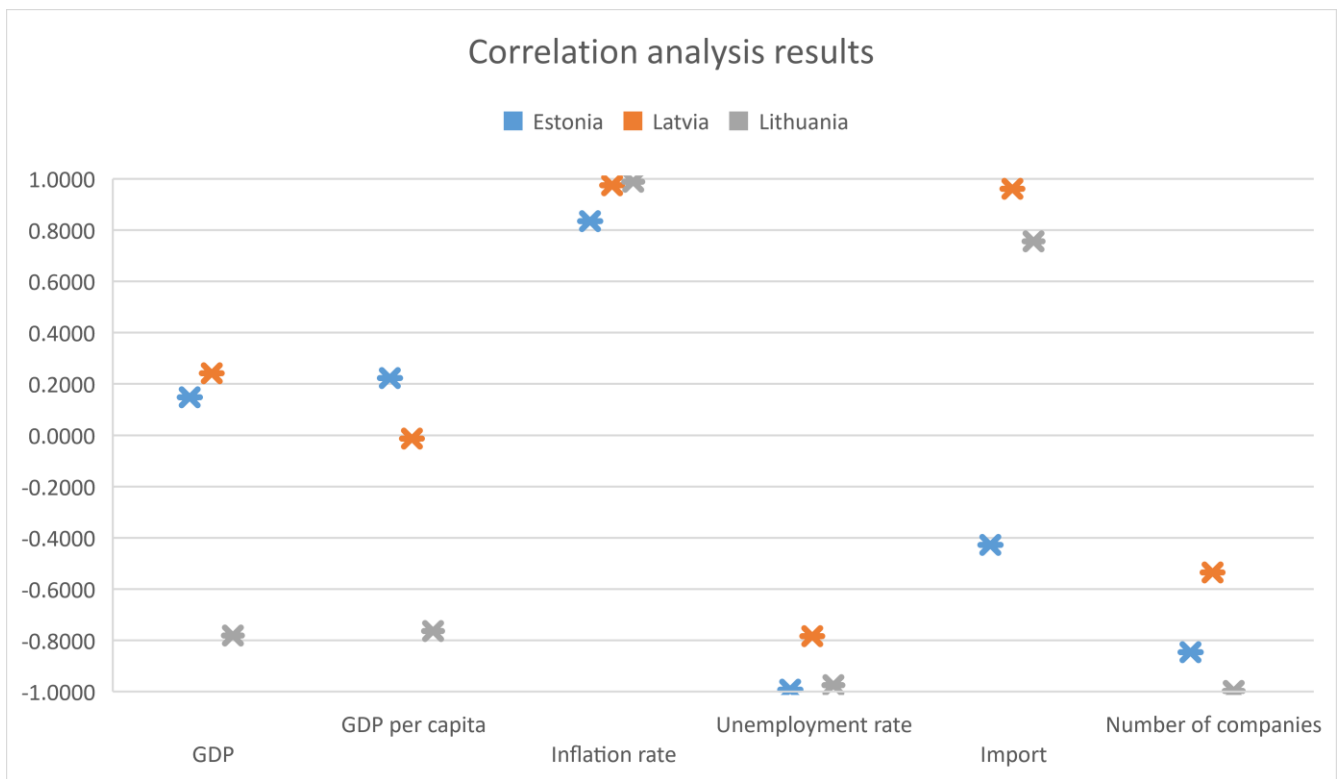


Fig. 24. Correlation analysis results (designed by author)

Correlation analysis results show that the dependence between the number of insolvencies and macroeconomic indicators varies across countries. In Estonia, the most influential factors are inflation rate, unemployment rate and the total number of companies. In Latvia, the number of insolvencies is mostly affected by inflation and unemployment rates, as well as by county's imports. In Lithuania, as shows correlation analysis, all the factors influence the total number of insolvencies. In general, the positive correlation between the inflation rate and the number of insolvent companies could be explained by worsening economic conditions, particularly if the inflation rate rises – materials, labour, and other services become more expensive, and companies may be forced to reduce production volume, resulting in a decrease in revenues and as an outcome – lack of working capital, cash flow problems and, usually, insolvency. The unexpected relationship is between the unemployment rate and the number of insolvent businesses. Typically, it should be obvious that when there are more bankrupt companies, the number of laid-off workers rises, and the unemployment rate rises as well, however, the strong negative correlation shows the opposite. The connection between imports level and the number of insolvent companies can be explained as follows: when the level of imports rises, there are more substitute products or services on the market, the consumption of domestic products and services can fall what results in an increase of a number of insolvent enterprises. However, Lithuania's case is the most interesting as each of the factors has a strong correlation with a number of insolvencies, even the GDP and GDP per capita indicators, which show the weak correlation in Latvia and Estonia. One of the reasons possibly could be the data set distribution, as in Lithuania the number of insolvent enterprises in 2020 has fallen by 50%. The other possible explanation could be that in Lithuania, in comparison to other Baltic states, the total number of companies is the lowest, however, the number of insolvent companies is the highest.

4.2. Calculation and analysis of financial indicators

The solvency, liquidity and profitability ratios were calculated separately for every company for the 2018-2020 years period, detailed calculations are provided in Appendices 4 and 5. For data comparison five sectors with the largest number of companies were chosen:

- Food, beverage and Tobacco;
- Consumer products and services;
- Utilities;
- Construction and materials;
- Industrial goods and services.

The ratio analysis by sector includes maximum, minimum, average, standard deviation, and median values calculation for each ratio in the 2018-2020 years period. The following results were obtained:

Table 11. Solvency and liquidity ratios analysis by sector (designed by author)

		Current ratio	Quick ratio	Operating cash flow ratio	Debt-to-Assets ratio	Debt-to-equity ratio
Maximum	Food, Beverage and Tobacco	14.11	6.00	1.14	0.65	1.92
	Consumer Products and Services	3.37	1.26	1.49	1.00	213.29
	Utilities	4.16	3.08	2.32	0.58	1.42
	Construction and Materials	2.84	1.26	0.81	0.72	2.79
	Industrial Goods and Services	4.75	4.65	2.03	0.71	2.48
Minimum	Food, Beverage and Tobacco	0.64	0.27	-0.60	0.06	0.06
	Consumer Products and Services	0.32	0.13	-0.12	0.33	0.52
	Utilities	0.46	0.46	0.36	0.17	0.21
	Construction and Materials	0.75	0.53	-0.50	0.39	0.65
	Industrial Goods and Services	1.23	0.88	-0.13	0.32	0.47
Average	Food, Beverage and Tobacco	3.06	1.47	0.29	0.41	0.93
	Consumer Products and Services	1.23	0.53	0.34	0.64	14.09
	Utilities	1.78	1.34	0.75	0.41	0.79
	Construction and Materials	1.69	0.91	0.06	0.57	1.57
	Industrial Goods and Services	1.81	1.59	0.98	0.44	0.96
Standard deviation	Food, Beverage and Tobacco	3.78	1.65	0.39	0.20	0.63
	Consumer Products and Services	0.78	0.31	0.38	0.18	48.33
	Utilities	1.33	0.89	0.52	0.13	0.37
	Construction and Materials	0.73	0.24	0.35	0.12	0.75
	Industrial Goods and Services	1.05	1.11	0.72	0.14	0.70
Median	Food, Beverage and Tobacco	1.38	0.74	0.21	0.54	1.18
	Consumer Products and Services	0.99	0.46	0.25	0.66	14.09
	Utilities	1.09	0.98	0.56	0.46	0.85
	Construction and Materials	1.63	0.85	0.03	0.54	1.21
	Industrial Goods and Services	1.47	1.24	1.06	0.40	0.66

Analyzing the current ratio indicator across five sectors it is noticeable that the widest range, the highest average value, and the standard deviation is in food, beverage and tobacco sector, also it is worth mentioning that data is widely spread out. The lowest minimum value for current ratio comes from

consumer products and services sector, this sector also has the lowest average and median values of current ratio. The overall tendency shows that most of the companies of the selected sectors do not face any difficulties with financing short-term liabilities. Investigating the quick ratio tendencies, it can be observed that the widest range, as well as the highest maximum value, exists in the food, beverage and tobacco sector. The lowest minimum value and the lowest median value is in the consumer products and services sector. The tendency for these two ratios is remarkably similar what means that liquidity problems are common for the consumer products and services sector. The operating cash flow ratio shows different trends, for this ratio, the widest ranges are in utilities and industrial goods and services sectors. The minimum amount of operating cash ratio is negative in four sectors out of five. The highest maximum value for this ratio is in the utilities sector. The values in industrial goods and services are extensively spread out. The highest median value exists in the industrial goods and services sector. The general tendency for operating cash flow ratio among all sectors shows that companies frequently face cash-flow problems. The debt-to-assets ratio is considered acceptable when its value is below 0.5. The lowest minimum value for debt-to-assets ratio is found in the food, beverage and tobacco sector, also this sector excels the lowest average as well as utilities sector, and the widest spread of data. This means that in the food, beverage and tobacco sector debts are relatively low in comparison with assets. The highest maximum value and highest median are found in the consumer products and services sector. The debt-to-equity ratio is considered good if its value is lower than 2. The highest debt-to-equity ratio occurs in the consumer products and services sector and it relates to one company, for this reason, the average and standard deviation values are also the highest in this sector. The lowest minimum value found in the food, beverage and tobacco sector, and the lowest median value in the industrial goods and services sector. After calculation of profitability ratios, the following results were obtained:

Table 12. Profitability ratios analysis by sector (designed by author)

		ROA	ROE	Net profit margin	EBIT margin
Maximum	Food, Beverage and Tobacco	10.49	0.23	0.14	0.16
	Consumer Products and Services	23.23	0.41	0.19	0.29
	Utilities	6.72	0.12	0.14	0.19
	Construction and Materials	8.54	0.15	0.07	0.08
	Industrial Goods and Services	7.11	0.16	0.42	0.40
Minimum	Food, Beverage and Tobacco	-3.72	-0.09	-0.11	-0.12
	Consumer Products and Services	-31.18	-73.14	-0.15	-0.08
	Utilities	-9.77	-0.20	-0.23	-0.09
	Construction and Materials	-12.75	-0.36	-0.13	-0.14
	Industrial Goods and Services	1.58	0.02	0.01	0.02
Average	Food, Beverage and Tobacco	2.88	0.04	0.03	0.03
	Consumer Products and Services	0.21	-4.15	0.01	0.04
	Utilities	1.75	0.02	0.03	0.05
	Construction and Materials	1.43	0.02	0.00	0.01
	Industrial Goods and Services	3.92	0.07	0.16	0.19
Standard deviation	Food, Beverage and Tobacco	3.94	0.07	0.05	0.05
	Consumer Products and Services	14.02	16.74	0.09	0.11

	Utilities	4.14	0.08	0.09	0.07
	Construction and Materials	6.39	0.16	0.06	0.06
	Industrial Goods and Services	1.71	0.04	0.14	0.15
Median	Food, Beverage and Tobacco	2.42	0.03	0.02	0.02
	Consumer Products and Services	1.94	0.05	0.01	0.03
	Utilities	2.15	0.04	0.06	0.05
	Construction and Materials	3.13	0.11	0.01	0.01
	Industrial Goods and Services	4.00	0.07	0.12	0.13

Analysing ROA ratio, it is noticeable the widest range for values in consumer products and services sector. This sector also excels the highest data spread out, the lowest average and median amount. In four sectors out of five analysed the minimum ROA values are negative, which means that some companies in sectors have losses during the analysed period. The industrial goods and services sector excels the highest median value as well as lowest standard deviation, and highest minimum value. Companies from the industrial goods and services sector did not face losses during the analysed period. The ROE ratio data analysis trends are remarkably like ROA data trends because for ratio calculation the same parameter of net profit is used. Examining ROE data trends, it is noticeable that the widest range for values is in the consumer products and services sector, this sector also excels the lowest average and largest data spread. The highest maximum ROE value indicated in the food, beverage and tobacco sector. The lowest median value indicated in two sectors: construction and materials, consumer products and services. The general trend for ROE indicator across all the sectors is its relatively low values, and the explanation could be that it is a general trend for manufacturing companies to have low ROE indicator. The next analysed profitability indicator was the net profit margin. This indicator considered as average when it stands at a 10% level, the higher value considered as good. The trend for net profit margin indicator is like other profitability indicators as in calculations is used the net profit value. For such sectors as food, beverage and tobacco, consumer products and services, utilities and construction and materials the lowest minimum values were negative during the analysed period, due to losses occurred. The widest range of indicator values is identified in the industrial goods and services sector. The median values in consumer goods and services and construction and materials sectors are close to zero, which means that in these sectors some companies are unprofitable. Analysis of the last indicator EBIT margin shows the same trends as net profit margin indicator when the industrial goods and services sector can be assessed as the most profitable, however, this sector also excels the widest data spread out, and the highest average value. The construction and materials sector shows the lowest EBIT margin profitability in comparison with other sectors. Summarizing, the noticeable thing is that the sector of industrial goods and services looks like the most stable, characterized by the lowest fluctuations. Moreover, for companies operating in the Baltic states, it is a common problem the negative values of ROA and ROE indicators.

After solvency, liquidity and profitability ratios calculation, the companies can be divided into four groups, the number of companies in each sector belonging to one of four groups is specified below:

Table 13. Companies' assessment by sector and group (designed by author)

		Profitable		Unprofitable	
		Sector	Number of companies	Sector	Number of companies
Solvent	Food, Beverage and Tobacco		3	Food, Beverage and Tobacco	3
	Basic Resources		1	Basic Resources	1
	Construction and Materials		1	Consumer Products and Services	1
	Consumer Products and Services		1	Health Care	1
	Energy		1	Industrial Goods and Services	1
	Health Care		1	Media	1
	Industrial Goods and Services		2	Real Estate	1
	Telecommunications		1	Retail	1
	Utilities		2	Telecommunications	1
	Total		13	Total	13
Insolvent	Consumer Products and Services		1	Food, Beverage and Tobacco	3
	Total		1	Consumer Products and Services	3
				Construction and Materials	2
				Real Estate	2
				Retail	1
				Travel and Leisure	1
				Technology	1
			Total	13	
Grand Total		14	Grand Total	26	

The general trend shows that there are more unprofitable than profitable companies in the market, however, the number of companies facing solvency problems is lower than solvent companies. The number of solvent, but unprofitable companies is equal to the number of companies that are insolvent and unprofitable. Only one company is identified as insolvent, but profitable. There is no general trend by sector in which the company operates, it is noticeable that there is an equal number of companies that are solvent and profitable or unprofitable in food, beverage and tobacco; basic resources; health care; utilities sectors. While the sectors as real estate and retail can generally be classified as unprofitable. The assessment of companies by group is provided in Appendix 7.

4.3. Insolvency assessment by Kralicek DF indicator

Using the data from the Balance sheet, Profit and Loss and Cash flow statements, with the Kralicek DF indicator score test, the following results were obtained:

Table 14. Kralicek DF indicator score test results (designed by author)

	2018							2019							2020						
	X1	X2	X3	X4	X5	X6	DF	X1	X2	X3	X4	X5	X6	DF	X1	X2	X3	X4	X5	X6	DF
Maximum	0.58	17.44	0.39	0.40	4.80	0.39	4.98	0.41	17.67	0.28	0.40	3.00	0.28	3.54	0.92	14.42	0.25	0.32	3.03	0.25	4.63
Minimum	-2.11	1.00	-0.11	-5.00	0.00	-0.11	-24.66	-0.51	1.21	-0.12	-11.00	0.00	-0.12	-54.26	-0.13	1.08	-0.22	-2.13	0.00	-0.22	-11.91
Average	-0.07	2.94	0.04	-0.08	0.37	0.04	0.24	-0.02	2.77	0.03	-0.22	0.29	0.03	-0.46	0.11	2.67	0.04	-0.01	0.27	0.04	0.80
Standard deviation	0.375	2.601	0.077	0.794	0.812	0.077	4.179	0.147	2.626	0.066	1.729	0.498	0.066	8.682	0.210	2.160	0.071	0.385	0.490	0.071	2.526
Median	0.00	2.27	0.03	0.03	0.16	0.03	0.93	0.00	1.92	0.03	0.03	0.14	0.03	0.74	0.03	1.95	0.04	0.04	0.14	0.04	1.05

It is visible the widest range for the value X2 during all analyzed periods. It could also be noticed that there is a great number of values equal to zero for parameter X1 in 2018 and 2019. DF indicator maximum value decreased in 2019 compared to 2018 and increased in 2020. The minimum value of DF indicator varied significantly during 2018-2020.

The assessment for companies, based on Kralicek DF indicator appears as following in Table 15:

Table 15. Kralicek DF indicator test assessment by number of companies (designed by author)

	2018	2019	2020
Excellent	2	2	2
Very good	1	3	4
Good	6	6	9
Average	9	4	5
Bad	10	13	13
Beginning of insolvency	3	4	2
Moderate insolvency	6	6	1
The striking insolvency	3	2	4
Total	40	40	40

Kralicek DF indicator has a wide system of grades and lets determine the company's financial state more precisely. The main advantage of this model is the opportunity to assess the level of insolvency including identification of the beginning of insolvency or its latest stage. Generally, companies that are assessed from average to excellent can be identified as healthy, and companies that are assessed as bad and lower can be defined as unhealthy. Based on this it is noticeable that the number of companies that can be defined as healthy is lower than the number of companies facing financial problems. Moreover, the number of companies assessed as bad or striking insolvency is increasing. The number of companies with excellent score remains stable, and the number of companies with a score good increased during the analyzed period. The analysis by sector of companies having the score from the striking insolvency to bad is provided in table 16:

Table 16. Kralicek DF score assessment by sector and number of companies (designed by author)

	2018		2019		2020	
	Sector	Number of companies	Sector	Number of companies	Sector	Number of companies
Bad	Basic Resources	1	Construction and Materials	1	Construction and Materials	1
	Construction and Materials	1	Consumer Products and Services	2	Consumer Products and Services	3
	Consumer Products and Services	1	Food, Beverage and Tobacco	3	Food, Beverage and Tobacco	4
	Food, Beverage and Tobacco	3	Health Care	1	Health Care	1
	Health Care	1	Industrial Goods and Services	2	Industrial Goods and Services	1
	Media	1	Media	1	Media	1
	Travel and Leisure	1	Technology	1	Technology	1
	Utilities	1	Travel and Leisure	1	Retail	1
Beginning of insolvency			Utilities	1		
	Food, Beverage and Tobacco	1	Basic Resources	1	Consumer Products and Services	1
	Industrial Goods and Services	1	Food, Beverage and Tobacco	2	Utilities	1
	Utilities	1	Utilities	1		
Moderate insolvency	Construction and Materials	1	Construction and Materials	1	Food, Beverage and Tobacco	1
	Consumer Products and Services	2	Consumer Products and Services	2		
	Food, Beverage and Tobacco	2	Food, Beverage and Tobacco	1		
	Utilities	1	Utilities	1		
			Telecommunications	1		
The striking insolvency	Consumer Products and Services	1	Consumer Products and Services	1	Construction and Materials	1
	Real Estate	1	Real Estate	1	Real Estate	2
	Telecommunications	1			Travel and Leisure	1

For three years period, the number of companies and sectors varies among the assessed score by the Kralicek DF indicator. There is no widespread trend related to the sector in which the company operates, which means that this model is suitable for all sectors. It can be observed that the number of companies assessed as bad in the consumer products and services sector is increasing, also the number of companies in the beverage, food and tobacco sector increased in 2020. However, the number of companies assessed as in a moderate insolvency state decreased in 2020. The score of travel and leisure service decreased from bad to the striking insolvency in 2020 and that could be related to the COVID-19 pandemic and the general worsening of the situation in this sector.

4.4. Bankruptcy prediction using Taffler and Tisshaw model

Using the data from the Balance sheet and Profit and Loss statements, with the Taffler and Tisshaw score test, the following results were obtained:

Table 17. Taffler and Tisshaw test results (designed by author)

	2018					2019					2020				
	X1	X2	X3	X4	Taffler score	X1	X2	X3	X4	Taffler score	X1	X2	X3	X4	Taffler score
Maximum	1.50	14.00	0.92	2.98	1.87	1.60	14.11	0.80	2.31	2.25	1.10	12.08	0.64	2.34	2.16
Minimum	-0.72	0.04	0.05	0.01	-0.30	-0.53	0.03	0.05	0.00	-0.23	-0.53	0.03	0.05	0.03	-0.20
Average	0.13	1.50	0.28	1.09	0.49	0.20	1.30	0.28	0.98	0.48	0.22	1.21	0.25	0.89	0.46
Standard deviation	0.403	2.306	0.176	0.689	0.374	0.416	2.220	0.173	0.542	0.392	0.322	1.917	0.145	0.541	0.355
Median	0.06	0.78	0.25	1.18	0.51	0.11	0.56	0.24	1.13	0.47	0.17	0.57	0.22	0.96	0.44

It is noticeable the largest range for a parameter X2 during the analyzed period. The median Taffler score is decreasing for 2018-2020 years, it might be identified as an overall deterioration in market conditions and the possibility for more companies to face financial difficulties. Moreover, according to the standard deviation score, it can be recognized that the values of parameters X1, X3 and X4 and Taffler score are close to the average value, however, the values of parameter X2 varies considerably.

The assessment for companies, based on Taffler and Tisshaw score appears as following in Table 18:

Table 18. Taffler and Tisshaw score test assessment by a number of companies (designed by author)

	2018	2019	2020
Bankrupt	6	9	6
Company in bankruptcy	5	4	4
Low likelihood of bankruptcy	29	27	30
Total	40	40	40

It is remarkable that the largest number of companies facing financial difficulties, as well as bankrupt, by Taffler and Tisshaw score was in 2019. As an advantage of Taffler and Tisshaw score assessment can be named the different levels of evaluation, so that not only the companies that already are in financial distress can be identified, but also the companies that could possibly face financial problems in the future. Table 19 provides the information how many companies from each sector can face financial distress.

Table 19. Number of companies by sector facing financial distress by Taffler and Tisshaw model (designed by author)

	2018		2019		2020	
	Sector	Number of companies	Sector	Number of companies	Sector	Number of companies
Bankrupt	Energy	1	Food, Beverage and Tobacco	1	Food, Beverage and Tobacco	1
	Food, Beverage and Tobacco	1	Consumer Products and Services	1	Technology	1
	Technology	1	Technology	1	Utilities	1
	Utilities	2	Utilities	3	Real Estate	2
	Real Estate	1	Industrial Goods and Services	1	Travel and Leisure	1
			Real Estate	2		
Company in bankruptcy	Real Estate	1	Energy	1	Energy	1
	Media	1	Real Estate	1	Consumer Products and Services	1
	Consumer Products and Services	1	Media	1	Media	1
	Travel and Leisure	1	Travel and Leisure	1	Construction and Materials	1
	Food, Beverage and Tobacco	1				

It can be observed that some sectors have a higher probability to face financial distress. There is one company in the media sector, however, each year it is identified as a company in bankruptcy. The real estate sector, according to Taffler and Tisshaw model looks also unsafe. The company from the travel and leisure sector in 2018 and 2019 was identified as a company in bankruptcy, however, in 2020 its score decreased and now it is identified as bankrupt.

4.5. Bankruptcy prediction using Springate model

Using the data from the Balance sheet and Profit and Loss statements, with the Springate score test, the following results were obtained:

Table 20. Springate test results (designed by author)

	2018					2019					2020				
	X1	X2	X3	X4	Springate score	X1	X2	X3	X4	Springate score	X1	X2	X3	X4	Springate score
Maximum	0.79	0.39	1.55	2.98	3.01	0.74	0.28	1.66	2.31	2.58	0.77	0.25	1.50	2.34	2.43
Minimum	-0.26	-0.11	-0.53	0.01	-0.46	-0.54	-0.12	-0.42	0.00	-0.43	-0.22	-0.22	-0.44	0.03	-1.12
Average	0.16	0.04	0.20	1.09	0.84	0.11	0.03	0.23	0.98	0.76	0.13	0.04	0.25	0.89	0.77
Standard deviation	0.225	0.077	0.359	0.689	0.614	0.267	0.066	0.425	0.542	0.633	0.234	0.071	0.388	0.541	0.659
Median	0.08	0.03	0.12	1.18	0.91	0.03	0.03	0.11	1.13	0.84	0.04	0.04	0.19	0.96	0.86

The analysis shows that the widest range for Springate score was in 2018, the score itself was decreasing during the period 2018-2020. Assessing the parameters range the widest was for parameter X4. Moreover, this parameter has the highest median value. The reason could possibly be the indicators used to calculate X4. For X4 calculation the amounts of total assets and sales are used, and usually, the amount of total assets is higher than the sales amount, at least for some companies.

Table 21. Springate score test assessment by a number of companies (designed by author)

	2018	2019	2020
Possible financial distress	18	23	20
Good financial health	22	17	20
Total	40	40	40

The Springate score assesses companies only if two groups: with possible financial distress or healthy. It is visible that a number of companies with possible financial problems was the largest in 2019, it

decreased in 2020, though, the amount of financially healthy and unhealthy companies is equal. It is also perceptible that the Springgate score test is stricter than Taffler and Tisshaw test because overall number of companies in financial distress is higher.

Table 22. Number of companies by sector facing financial distress by Springgate model (designed by author)

	2018		2019		2020	
	Sector	Number of companies	Sector	Number of companies	Sector	Number of companies
Possible financial distress	Consumer Products and Services	3	Consumer Products and Services	5	Construction and Materials	1
	Energy	1	Energy	1	Consumer Products and Services	5
	Food, Beverage and Tobacco	3	Food, Beverage and Tobacco	4	Energy	1
	Health Care	1	Health Care	1	Food, Beverage and Tobacco	3
	Industrial Goods and Services	1	Industrial Goods and Services	2	Industrial Goods and Services	1
	Media	1	Media	1	Media	1
	Real Estate	3	Real Estate	3	Real Estate	2
	Technology	1	Technology	1	Retail	1
	Travel and Leisure	1	Telecommunications	1	Technology	1
	Utilities	3	Travel and Leisure	1	Travel and Leisure	1
		Utilities	3	Utilities	3	

The Springgate model shows possible financial distress for companies operating in almost all examined sectors. In some sectors like consumer products and services, food, beverage and tobacco, industrial goods and services the number of companies in possible financial distress varies yearly, however, other sectors like utilities, media, energy, health care show the same number of companies that are unhealthy financially. Additionally, in 2020 companies from sectors such as construction and material, travel and leisure were assessed as facing possible financial distress, these sectors were assessed as healthy in 2018 and 2019. The main disadvantage of the Springgate model is that the level of financial distress cannot be identified.

4.6. Bankruptcy prediction using Zmijewski model

Using the data from the Balance sheet and Profit and Loss statements, with the Zmijewski score test, the following results were obtained:

Table 23. Zmijewski test results (designed by author)

	2018				2019				2020			
	X1	X2	X3	Zmijewski score	X1	X2	X3	Zmijewski score	X1	X2	X3	Zmijewski score
Maximum	0.24	1.00	14.00	2.91	0.23	0.83	14.11	1.12	0.14	0.92	12.08	2.36
Minimum	-0.34	0.06	0.42	-4.00	-0.22	0.06	0.23	-4.18	-0.31	0.07	0.22	-4.21
Average	0.02	0.45	2.07	-1.82	0.02	0.48	1.88	-1.66	0.02	0.49	1.91	-1.64
Standard deviation	0.084	0.186	2.262	1.286	0.074	0.180	2.242	1.210	0.072	0.191	1.976	1.279
Median	0.03	0.44	1.33	-1.90	0.02	0.52	1.15	-1.53	0.04	0.51	1.22	-1.65

It is visible a large range for the value X3 in every analyzed year. The other characteristic is that the average of the X1 parameter is equal to 0.02 during all analyzed periods. The maximum value of the Zmijewski test varies significantly during the period, it decreased more than twice in the year 2019, comparing to the year 2018, however, the increase in the year 2020, comparing with 2019 was more than twice. Although, the data of parameters X3 and Zmijewski score is widely spread out.

The assessment for companies, based on the Zmijewski score appears as following in Table 24:

Table 24. Zmijewski score test assessment by a number of companies (designed by author)

	2018	2019	2020
Possible financial distress	3	3	3
Good financial health	37	37	37
Total	40	40	40

Zmijewski test score assessment shows that every year the number of companies in possible financial distress and healthy companies is equal to 3 and 37 accordingly. This number is the lowest comparing with Taffler and Tisshaw and Springate scores. Table 25 provides information on which sectors can face financial distress.

Table 25. Number of companies by sector facing financial distress by Zmijewski model (designed by author)

	2018		2019		2020	
	Sector	Number of companies	Sector	Number of companies	Sector	Number of companies
Possible financial distress	Consumer Products and Services	3	Real Estate	1	Real Estate	1
			Consumer Products and Services	2	Consumer Products and Services	2

Only 3 companies by Zmijewski score assessment are classified as facing financial difficulties. In 2018 all companies belong to the consumer products and services sector, in 2019 and 2020 the number of companies in the consumer products and services sector decreased to 2 and 1 company from the real estate sector appeared. Noticeable that the Zmijewski score model does not assess companies from manufacturing, construction or utilities sectors as potentially facing financial distress as it was assessed by other models as Springate or Taffler and Tisshaw. The results of the Zmijewski score cannot be assessed as highly reliable, likely that this model will not be suitable as an additional tool for the insolvency assessment.

4.7. Bankruptcy prediction using Altman II model

Using the data from the Balance sheet and Profit and Loss statements, with the Altman II score test, the following results were obtained:

Table 26. Altman II test results (designed by author)

	2018						2019						2020					
	X1	X2	X3	X4	X5	Altman II score	X1	X2	X3	X4	X5	Altman II score	X1	X2	X3	X4	X5	Altman II score
Maximum	0.79	0.66	0.39	16.56	2.98	8.71	0.74	0.71	0.28	16.67	2.31	8.95	0.77	0.81	0.25	13.42	2.34	7.67
Minimum	-0.26	-0.86	-0.11	0.00	0.01	-0.45	-0.54	-0.95	-0.12	0.21	0.00	-0.57	-0.22	-1.01	-0.22	0.08	0.03	-0.56
Average	0.16	0.19	0.04	1.93	1.09	2.28	0.11	0.17	0.03	1.75	0.98	2.05	0.13	0.19	0.04	1.67	0.89	1.96
Standard deviation	0.225	0.296	0.077	2.619	0.689	1.515	0.267	0.303	0.066	2.635	0.542	1.503	0.234	0.314	0.071	2.162	0.541	1.376
Median	0.08	0.24	0.03	1.25	1.18	2.28	0.03	0.20	0.03	0.89	1.13	1.93	0.04	0.19	0.04	0.95	0.96	1.75

The widest range has the parameter X4, during all analyzed period, also the values for this parameter are spread out widely. The maximum and minimum values for the Altman II score do not vary significantly, however, the maximum value is appreciably higher than the average amount.

The assessment for companies, based on Altman II score appears as following in Table 27:

Table 27. Altman II score test assessment by a number of companies (designed by author)

	2018	2019	2020
Good financial health	7	9	9
Possible financial distress	9	14	14
Grey area	24	17	17
Total	40	40	40

Altman II model assesses companies into 3 main groups, it is visible that a group of companies identified as the grey area is the largest during all analyzed periods. The number of companies with good financial health increased in 2019 comparing to 2018 and remained stable in 2020. Comparing to other models like Springate, Taffler and Tisshaw or Zmijewski, the number of companies with good financial health is the lowest according to Altman's model. Table 28 provides the information on sectors and the number of companies that are classified as facing financial distress.

Table 28. Number of companies by sector facing financial distress by Altman II model (designed by author)

	2018		2019		2020	
	Sector	Number of companies	Sector	Number of companies	Sector	Number of companies
Possible financial distress	Consumer Products and Services	1	Consumer Products and Services	3	Construction and Materials	1
	Energy	1	Energy	1	Consumer Products and Services	2
	Food, Beverage and Tobacco	1	Food, Beverage and Tobacco	1	Energy	1
	Industrial Goods and Services	1	Industrial Goods and Services	2	Food, Beverage and Tobacco	1
	Real Estate	3	Real Estate	3	Industrial Goods and Services	2
	Utilities	2	Technology	1	Real Estate	2
			Utilities	3	Technology	1
					Travel and Leisure	1
				Utilities	3	

Visible, that sectors which according to Altman's model faces financial distress in 2018 are all in the same group in 2019 and 2020 as well. In 2020 more different sectors could face financial distress than in 2018 and 2019. The general trend of the Altman II score assessment is that manufacturing companies are identified as facing financial distress. The results of the Altman II model assessment by sectors are similar to the results provided by Springate, Taffler and Tisshaw models, where such sectors as utilities, travel and leisure, technology were identified as risky. The similarity with the Zmijewski score model excels in the identification of the real estate sector and companies belonging to it as facing financial distress. The main limitation of the Altman II model remains the assessment of the grey area, as the model does not provide the precise description of financial distress probability on these companies, the lack of information in the description of the Altman II model does not let to decide which further methods could be valuable in assessing the financial risks of companies in a grey area, as well as there is no possibility to evaluate when the companies could face further financial difficulties.

4.8. Bankruptcy prediction using Grover model

Using the data from the Balance sheet and Profit and Loss statements, with the Grover score test, the following results were obtained:

Table 29. Grover score test results (designed by author)

	2018			2019			2020		
	X1	X2	Grover score	X1	X2	Grover score	X1	X2	Grover score
Maximum	0.79	0.39	1.78	0.74	0.28	1.61	0.77	0.25	1.72
Minimum	-0.26	-0.11	-0.47	-0.54	-0.12	-1.10	-0.22	-0.22	-1.07
Average	0.16	0.04	0.41	0.11	0.03	0.35	0.13	0.04	0.40
Standard deviation	0.225	0.077	0.440	0.267	0.066	0.555	0.234	0.071	0.542
Median	0.08	0.03	0.31	0.03	0.03	0.31	0.04	0.04	0.37

It is noticeable that ranges for X1 and X2 parameters are not very wide. Moreover, the median for parameters X1 and X2 are similar during the 2018-2020 years period. Additionally, the Grover score meaning is equal in the year 2018 and year 2019, and slightly higher in the year 2020.

The assessment for companies, based on Grover score appears as following in Table 30:

Table 30. Grover score test assessment by a number of companies (designed by author)

	2018	2019	2020
Bankrupt companies	5	8	6
Healthy companies	35	32	34
Total	40	40	40

Grover score assessment shows that in the year 2018 there were 35 healthy companies and 5 close to bankruptcy. In the year 2019 the number of healthy companies decreased and concluded 32 companies, the number of financially unstable increased to 8 companies. In the year 2020, the number of financially unstable companies decreased, comparing to the year 2019, however, it was still higher than in the year 2018. The number of financially healthy companies in the year 2020 accounted for 34. Table 31 provides the information on which sectors are classified as facing financial distress.

Table 31. Number of companies by sector facing financial distress by Grover model (designed by author)

	2018		2019		2020	
	Sector	Number of companies	Sector	Number of companies	Sector	Number of companies
Bankrupt companies	Consumer Products and Services	2	Consumer Products and Services	3	Consumer Products and Services	2
	Food, Beverage and Tobacco	1	Food, Beverage and Tobacco	2	Food, Beverage and Tobacco	1
	Real Estate	1	Real Estate	2	Real Estate	2
	Utilities	1	Utilities	1	Travel and Leisure	1

According to Grover model, only one company is evaluated as having possible financial problems throughout each year during the period 2018-2020 - Rīgas autoelektroaparātu rūpnīca, all other companies vary yearly. The sectors that could face financial distress in 2018 and 2019 are the same, the only change in 2020 is the replacement of utilities sector by travel and leisure. This model does not estimate financial problems in other sectors like energy, technology, telecommunications or industrial goods and services which were assessed as facing financial distress by other models. The main limitation of the Grover model is the assessment scale, when a company can be either bankrupt or healthy, with no interim results or stages.

4.9. Bankruptcy prediction using Grigaravicius model

The calculation process of the Grigaravicius bankruptcy prediction model faced the following limitations: if a company does not have financial liabilities or if current assets are almost equal to current liabilities the further calculation cannot be performed. For this reason, the companies for which the Grigaravicius score or P value cannot be calculated were omitted. The total number of companies analyzed using the Grigaravicius model was 34.

Using the data from the Balance sheet and Profit and Loss statements, with the Grigaravicius score test, the following results were obtained:

Table 32. Grigaravicius score test results (designed by author)

	2018									2019									2020								
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X1	X2	X3	X4	X5	X6	X7	X8	X9	X1	X2	X3	X4	X5	X6	X7	X8	X9
Maximum	4.75	0.48	214.29	457.67	0.39	0.40	0.24	46.15	2.98	4.16	0.65	8.54	64.31	0.28	0.40	0.23	34.63	1.90	5.35	0.60	12.83	80.91	0.25	0.32	0.14	27.63	1.62
Minimum	0.42	-0.26	1.28	0.06	-0.11	-5.00	-0.34	-91.97	0.01	0.23	-0.54	1.21	0.47	-0.12	-11.00	-0.22	#####	0.00	0.22	-0.22	1.21	0.24	-0.22	-2.13	-0.31	-134.55	0.03
Average	1.69	0.14	8.20	21.13	0.04	-0.09	0.02	3.92	1.06	1.55	0.08	2.41	7.94	0.04	-0.26	0.02	-47.56	0.94	1.69	0.11	2.51	6.63	0.04	-0.02	0.02	-3.02	0.83
Standard deviation	0.982	0.186	35.880	76.592	0.083	0.860	0.091	22.938	0.679	1.06	0.25	1.43	13.99	0.07	1.87	0.08	275.75	0.50	1.159	0.209	2.043	13.785	0.075	0.417	0.076	26.300	0.464
Median	1.33	0.10	1.81	3.40	0.03	0.03	0.02	3.59	1.20	1.21	0.03	2.13	2.39	0.03	0.04	0.02	2.17	1.18	1.27	0.04	2.05	2.12	0.04	0.05	0.04	1.96	0.96

The widest range is for variables X3, X4 and X8, the values for these parameters are widely spread out. The lowest median is for variables X2, X5, X6 and X7, their values are close to 0. This model uses the largest number of variables in comparison with other models. However, it is beside the purpose to calculate data ranges for the Grigaravicius score itself, because it will not show the reliable result, as for calculation of probability different formula is used.

The assessment for companies, based on the Grigaravicius score appears as following in Table 33:

Table 33. Grigaravicius score test assessment by a number of companies (designed by author)

	2018	2019	2020
Healthy company	24	19	19
High bankruptcy probability	10	15	15
Total	34	34	34

An assessment shows that the number of companies facing financial difficulties is increasing, in 2018 there were 10 companies in financial distress, however, the number became 1.5 times higher in 2019 and remained as high in 2020.

Table 34. Number of companies by sector facing financial distress by Grigaravicius model (designed by author)

	2018		2019		2020	
	Sector	Number of companies	Sector	Number of companies	Sector	Number of companies
High bankruptcy probability	Basic Resources	1	Consumer Products and Services	4	Construction and Materials	1
	Consumer Products and Services	3	Energy	1	Consumer Products and Services	3
	Energy	1	Food, Beverage and Tobacco	2	Food, Beverage and Tobacco	3
	Food, Beverage and Tobacco	2	Media	1	Media	1
	Real Estate	1	Real Estate	2	Real Estate	2
	Travel and Leisure	1	Retail	1	Retail	1
	Utilities	1	Technology	1	Technology	1
			Travel and Leisure	1	Travel and Leisure	1
			Utilities	2	Utilities	2

Noticeable, that companies from some sectors are assessed as having a high probability of bankruptcy every year. The number of companies in each sector can vary, however, the Grigaravicius model shows

a more precise assessment than, for example, Zmijewski model. This model can be compared with such bankruptcy prediction models as Springate or Altman II. The main disadvantage of Grigaravicius model is its calculation limitations, which were discussed above.

4.10. Comparison of the research results

Firstly, the results of the assessment by financial indicators and the Kralicek DF indicator will be compared. To make the results comparable, the average of the Kralicek DF indicator was calculated for the period 2018-2020.

Table 35. Comparison of the assessment by financial indicators and Kralicek DF indicator (designed by author)

	Excellent	Very good	Good	Average	Bad	Beginning of insolvency	Moderate insolvency	The striking insolvency
Solvent	Silvano Fashion Group	Grigeo	Amber Grid	Latvijas balzams	Ekspress Grupp	AUGA group	SAF Tehnika	
		Olainfarm	Apranga	Latvijas Gāze	Harju Elekter	LITGRID		
		Siguldas ciltslietu un mākslīgās apsēklošanas stacija	Arco Vara	Ignitis grupē	Kauno energija			
		Tallinna Sadam	Klaipēdos nafta	Merko Ehitus	Latvijas Jūras medicīnas centrs			
			Telia Lietuva		Linās Agro Group			
			Žemaitijos pienas		Linās			
					Rokiškio sūris			
Insolvent				Pieno žvaigždēs	HansaMatrix	PRFoods	Baltika	Pro Kapital Grupp
				Tallinna Kaubamāja Grupp	Nordecon	Tallink Grupp	Panevėžio statybos trestas	Rīgas autoelekroaparātu rūpnīca
					Vilniaus baldai		Nordic Fibreboard	
					Vilkyškių pieninė		Snaigė	

The main difference between the assessment using financial indicators and Kralicek DF indicators is the level of the insolvency risk assigned. Using financial indicators there were only two levels possible: solvent or insolvent. Moreover, assessing the company in three years period sometimes can be complicated, because the company's financial situation can change, as well as there is no general methodology on how a company should be valued if some indicators show a financially healthy state, while others are below the healthy range. The other limitation for using only financial indicators is the reviewer's objectivity, as the same indicators can be assessed differently. The comparison of the results provided by financial indicators assessment and Kralicek DF indicator assessment shows that some companies that were assessed as a solvent, however, can be in a bad or the beginning of insolvency state by Kralicek DF indicator. Companies that were assessed as insolvent after financial ratios analysis got the assessment score from average to the striking insolvency by Kralicek DF indicator. The research showed, that the Kralicek DF indicator model is suitable for the insolvency risk assessment of companies operating in the Baltic States. This model can be used as an additional assessment method to provide valuable insights on the company's solvency state. Besides, the Kralicek DF indicator is the only model that evaluates cash flow in a calculation. During the research, it was also noticed that companies operating in the Baltic States are usually facing cash flow problems, such as negative operating or net cash flow. A problem with cash flow and the lack of working capital is common for all sectors. Yet, neither financial indicators nor the Kralicek DF indicator does not evaluate the internal factors of the risk of insolvency. These indicators used together work excellent in identifying the financial problems of a company, however, they do not detect the reason why a company has a higher risk of insolvency. Finalizing the

results and combining the possibly insolvent companies by country and sector, the following data was obtained:

Table 36. Companies with the highest risk of insolvency by sector and country (designed by author)

	Estonia	Latvia	Lithuania
Basic Resources			Linās
Construction and Materials	Nordecon		Panevėžio statybos trestas
Consumer Products and Services	Baltika		Utenos trikotažas
	Nordic Fibreboard		Vilniaus baldai
			Snaigė
Food, Beverage and Tobacco	PRFoods		Linās Agro Group
			Rokiškio sūris
			AUGA group
			Vilkyškių pieninė
Health Care		Latvijas Jūras medicīnas centrs	
Industrial Goods and Services		Harju Elekter	
Media	Ekspress Grupp		
Real Estate	Pro Kapital Grupp	Rīgas autoelektroaparātu rūpnīca	
Technology		HansaMatrix	
Telecommunications		SAF Tehnika	
Travel and Leisure	Tallink Grupp		
Utilities			Kauno energija
			LITGRID

Comparing the total number of companies that were assessed and the results by country it is visible, that in Estonia 7 companies out of 13 can potentially be insolvent, in Latvia 5 companies out of 8, and in Lithuania 11 companies out of 19. The general result is that more than 50% of companies analysed that are listed on the NASDAQ Baltic stock exchange can potentially be insolvent.

Secondly, the results gained using bankruptcy prediction models are analysed. In the beginning, the models are compared in between. The comparison provided in Table 37.

The comparison between all bankruptcy prediction models applied shows that some of the models are more accurate than others. Zmijewski model can be identified as the less accurate because in comparison with other models it shows the lowest number of companies, that potentially can face financial distress. This model works the best for companies operating in the consumer products and services sector, however, should be avoided to apply for manufacturing companies. The other comparable models could be Taffler and Tisshaw and Springate, the models assess companies operating in utilities, real state, basic resources and construction and materials similarly, however, the assessment of companies operating in industrial goods and services or consumer goods and services varies. The other difference is that companies assessed as healthy by Taffler and Tisshaw model are assessed as having possible financial problems by the Springate model. The conclusion could be that for manufacturing companies, operating in the food, beverage and tobacco sector the Taffler and Tisshaw model is not suitable. The other model that's results differ is the Altman II model.

Table 37. The comparison of the results obtained by bankruptcy prediction models (designed by author)

		2018						2019						2020					
		Taffler	Sprinke	Znajewski	Altmann II	Grover	Griernavicius	Taffler	Sprinke	Znajewski	Altmann II	Grover	Griernavicius	Taffler	Sprinke	Znajewski	Altmann II	Grover	Griernavicius
Griseo	Basic Resources	0.56	1.10	-2.46	2.50	0.24	1.00	0.63	1.27	-2.89	2.85	0.57	0.00	0.66	1.27	-3.24	3.10	0.67	0.00
Linus	Basic Resources	0.77	1.18	-3.27	3.20	0.87	0.00	0.65	0.90	-3.04	2.96	0.79	0.00	0.80	1.18	-3.06	3.00	1.08	0.00
Merko Ehitus	Construction and Materials	0.65	1.41	-1.81	2.89	0.95	0.00	0.61	1.43	-1.59	2.55	1.33	0.00	0.69	1.50	-2.51	3.00	1.20	0.00
Nordecon	Construction and Materials	0.59	1.05	-0.60	2.56	0.21	0.00	0.56	0.95	-0.32	2.34	0.18	NA	0.61	1.00	-0.22	2.53	0.16	NA
Panevžio statybos trestas	Construction and Materials	0.49	0.92	-1.54	2.66	0.69	0.00	0.54	0.87	-1.25	2.26	0.57	0.00	0.24	-0.33	-0.15	0.90	-0.67	1.00
Baltika	Consumer Products and Services	0.55	0.64	2.91	2.25	-0.03	1.00	0.10	-0.07	-0.21	0.91	-0.50	1.00	0.29	0.62	0.56	1.02	0.09	1.00
Silveno Fashion Group	Consumer Products and Services	1.12	3.01	-3.51	4.21	1.78	1.00	1.24	2.58	-3.31	3.61	1.61	0.00	0.69	2.43	-2.64	3.53	1.72	0.00
Nordic Fibreboard	Consumer Products and Services	0.28	0.28	0.18	1.39	0.04	0.00	0.34	-0.27	1.12	0.75	-1.10	1.00	0.60	0.46	-1.21	1.75	-0.06	1.00
Snares	Consumer Products and Services	0.37	0.08	0.17	0.71	-0.47	1.00	0.33	-0.08	0.49	0.56	-0.70	1.00	0.33	0.58	0.09	1.01	0.17	0.00
Utenos trikotažas	Consumer Products and Services	0.50	0.95	-1.69	2.14	0.35	0.00	0.52	0.86	-1.47	1.97	0.42	0.00	0.38	0.82	-1.07	1.79	0.43	0.00
Vilnius baldai	Consumer Products and Services	0.57	1.18	-1.34	2.72	0.33	0.00	0.42	0.61	-0.85	1.77	0.03	1.00	0.33	0.62	-0.57	1.39	0.17	1.00
Amber Grid	Energy	-0.18	0.39	-1.38	0.82	0.13	1.00	0.24	0.32	-1.88	0.85	0.13	1.00	0.25	0.38	-1.65	0.79	0.24	0.00
AUGA group	Food, Beverage and Tobacco	0.14	-0.04	-1.49	0.74	0.04	0.00	0.13	0.18	-1.02	0.71	0.12	0.00	0.17	0.44	-1.12	0.90	0.33	0.00
Latvijas balzams	Food, Beverage and Tobacco	0.56	0.86	-3.12	2.67	0.71	0.00	0.71	1.03	-3.44	3.24	1.00	0.00	0.65	0.92	-3.34	3.01	0.98	0.99
Linus Agro Group	Food, Beverage and Tobacco	0.51	0.92	-1.22	2.32	0.39	0.00	0.52	0.86	-1.02	2.48	0.25	0.00	0.51	0.96	-1.26	2.38	0.41	0.00
PRFoods	Food, Beverage and Tobacco	0.47	0.87	-0.72	2.17	0.17	0.00	0.36	0.47	-0.49	1.53	-0.05	1.00	0.35	0.40	-0.44	1.46	-0.11	1.00
Pieno žvairėdės	Food, Beverage and Tobacco	0.55	1.01	-0.77	2.62	0.05	1.00	0.58	1.25	-1.08	2.84	0.31	NA	0.71	1.63	-1.69	3.22	0.53	NA
Rokiškio sūris	Food, Beverage and Tobacco	0.60	0.95	-3.03	3.26	0.74	0.00	0.66	1.07	-3.13	3.43	0.84	0.00	0.56	0.96	-2.91	2.94	0.77	0.00
Siguldas ciltšie tu un mašalīgās spēkleišēnas	Food, Beverage and Tobacco	1.87	1.41	-4.00	8.71	1.38	NA	2.25	2.16	-4.18	8.95	1.54	NA	2.16	2.37	-4.21	7.67	1.68	NA
Vilkyški pieninė	Food, Beverage and Tobacco	0.29	0.37	-0.72	1.65	-0.07	1.00	0.33	0.47	-0.85	1.90	-0.12	1.00	0.45	0.72	-1.42	2.26	-0.02	1.00
Žemaitijos pienas	Food, Beverage and Tobacco	0.71	1.39	-3.08	3.47	0.62	0.00	0.80	1.60	-2.95	3.37	0.93	0.00	0.81	1.57	-3.20	3.61	0.97	0.00
Latvijas Jūras medicīnas centrs	Health Care	0.31	0.49	-3.07	2.78	0.39	0.00	0.49	0.70	-3.14	2.91	0.44	0.00	0.51	0.90	-3.07	2.75	0.53	0.00
Clairfarm	Health Care	0.53	1.09	-2.98	2.79	0.57	0.00	0.87	1.86	-3.55	3.38	1.14	0.00	0.44	1.01	-3.18	2.79	0.42	0.00
Harju Eilekter	Industrial Goods and Services	0.48	0.83	-2.57	2.79	0.42	0.00	0.47	0.84	-2.25	2.62	0.39	0.00	0.51	0.94	-2.45	2.67	0.46	0.00
Klaipēdos nafta	Industrial Goods and Services	0.52	0.90	-2.60	1.51	0.53	0.00	0.11	0.30	-0.29	0.42	0.17	0.00	0.44	0.43	-0.73	0.51	0.24	0.00
Talfrma Sadam	Industrial Goods and Services	0.87	1.39	-2.14	1.13	0.32	0.00	0.92	1.46	-2.36	1.19	0.38	0.00	0.64	0.99	-2.22	1.04	0.26	0.00
Ekspres Grupp	Media	0.24	0.44	-2.35	1.83	0.14	0.00	0.25	0.41	-1.75	1.42	0.11	1.00	0.28	0.44	-2.03	1.51	0.14	1.00
Arco Vara	Real Estate	0.22	0.15	-0.74	0.50	0.27	0.00	0.30	0.62	-1.30	1.18	0.61	0.00	0.37	0.98	-1.64	1.51	0.95	0.00
Pro Kapital Grupp	Real Estate	0.43	0.31	-1.26	0.82	0.24	0.00	0.08	-0.07	0.04	0.56	-0.36	1.00	-0.09	-1.12	2.36	-0.48	-1.07	0.90
Rīgas autoelektroapārītu rūpnīca	Real Estate	-0.30	-0.46	-1.18	-0.45	-0.03	0.91	-0.23	-0.43	-1.12	-0.57	-0.14	0.86	-0.05	-0.42	-1.33	-0.56	-0.13	1.00
Aprana	Retail	0.98	2.12	-3.13	4.54	1.04	0.00	0.49	1.14	-1.06	2.16	0.51	0.00	0.38	0.98	-1.00	1.89	0.58	0.00
Talfrma Kaubemāja Grupp	Retail	0.58	1.19	-2.07	2.70	0.30	0.00	0.47	0.98	-1.36	2.12	0.32	1.00	0.37	0.72	-0.88	1.75	0.14	1.00
HansaMatrix	Technology	0.16	0.67	-0.71	1.33	0.22	NA	0.13	0.54	-0.36	1.19	0.15	NA	0.13	0.36	-0.25	1.07	0.02	1.00
SAF Tehnika	Telecommunications	1.04	1.31	-3.45	4.55	1.40	NA	0.50	0.85	-2.56	2.65	0.99	0.00	0.59	1.20	-2.37	2.48	1.13	0.00
Telia Lietuva	Telecommunications	0.54	1.11	-2.27	1.83	0.41	0.00	0.44	0.92	-2.05	1.65	0.46	0.00	0.46	0.96	-2.12	1.72	0.47	0.00
Talfrma Grupp	Travel and Leisure	0.27	0.55	-1.98	1.54	0.11	1.00	0.28	0.55	-1.81	1.45	0.11	1.00	-0.20	-0.45	-0.97	0.60	-0.28	1.00
Latvijas Gāze	Utilities	0.63	1.03	-3.18	2.68	0.59	0.00	0.70	0.95	-3.52	3.16	0.57	0.00	0.49	0.65	-3.43	2.83	0.50	0.00
Ieritis grupē	Utilities	0.07	0.20	-1.17	0.68	0.12	0.00	0.19	0.31	-1.09	0.65	0.11	1.00	0.38	0.98	-1.45	0.96	0.54	0.00
Kauno enerģija	Utilities	0.30	0.47	-2.19	1.23	0.19	0.00	0.14	0.14	-1.96	0.97	0.06	NA	0.11	0.11	-1.76	0.80	0.05	1.00
LITGRID	Utilities	-0.25	-0.17	-1.15	0.67	-0.06	1.00	0.17	-0.01	-1.63	0.85	-0.13	1.00	0.39	0.66	-1.89	1.20	0.20	1.00

Comparing it with the Springate model it can be seen that a certain number of companies assessed as healthy by the Springate model are in a grey area by the Altman II model. This model can be identified as suitable as an additional tool for the insolvency risk assessment, however, the main limitation of it remains the assessment of the grey area, because companies with this score need additional assessment procedures to identify and measure the risk of insolvency. The Grover score model results best to compare with Zmijewski model results, both models provide the lowest number of possible insolvencies assessed and show the same results in real estate and consumer product and services sectors. The Grover model similarly to the Zmijewski model works inappropriately for companies operating in the manufacturing industry. Though, for companies operating in the Baltic States Grover and Zmijewski models are not fully appropriate as the results obtained by other assessment methods varies significantly. The last Grigaravicius model shows results similar to the Altman II model between companies identified as facing financial distress, however, the model limitations and calculation difficulty do not let to presume that it is suitable as an additional tool for an insolvency risk assessment. Grigaravicius model requires a lot of data and it could be time-consuming for an assessor to obtain all data required, although in scientific research the model can be used.

Considering all the factors, it could be concluded that Springate and Altman II models work the best for companies operating in the Baltic States. These models can be used as an additional tool for insolvency assessment. The research also verified the assumption, provided in the scientific literature analysis, that bankruptcy prediction models work the best as the latest step in insolvency risk assessment, however, the accuracy level of the evaluation without using other tools such as financial indicators or Kralicek DF indicator would not be full and precise.

Conclusions and recommendations

1. The insolvency risk assessment problem analysis demonstrated the following points:
 - The term insolvency is usually described as the failure of a company to fulfil its obligations. Often there is confusion between terms insolvency and bankruptcy as the description varies depending on the jurisdictions, however, bankruptcy is more related to a legal process.
 - The consequences of corporate insolvency can be either negative or positive. Mostly, insolvency as a phenomenon is considered in a negative way because it leads to an overall worsening of a state of the economy by a decline in production, reduction of tax revenues, GDP, an increase of unemployment rate and formation of a multiplier effect. Nevertheless, the positive aspects of corporate insolvency could be the replacement of old companies with new and more technologically advanced ones, as well as an increase of competitiveness in a market.
 - The importance of insolvency risk assessment is reasonable in a rapidly changing economic environment. The recent unexpected events such as COVID-19 pandemic and worldwide lockdowns, despite the rapidly recovering economy, can have dramatic consequences soon. To prevent or be prepared for possible financial distress, companies should pay more attention to methods used for an insolvency risk assessment.
2. The general insolvency risk assessment methodologies suggest using several step models, which include the review of external and internal factors, financial ratios calculation and analysis as well as application of bankruptcy prediction models to evaluate an insolvency risk. The financial indicators used for insolvency risk assessment belong to solvency, liquidity, and leverage groups. These indicators measure company's ability to deal with short-term debts, evaluate the overall level of debt. Profitability ratios also can be used for a general financial health evaluation, moreover, that these ratios show the relationship with liquidity and solvency ratios. As the last step in insolvency risk assessment, the bankruptcy prediction models can be applied. Generally, these models are divided into 3 main groups: statistical, artificially intelligent expert system models (AIES), theoretical. Usually, researches are focused on the application of statistical bankruptcy prediction models and limited to a comparison between multiple discriminant analysis and logit or probit models. Kralicek insolvency tests are relatively new and still not widely used by researchers. The first Kralicek quick test was developed in 1990 and originally had four different parameters assessed, later the model was developed and became a model including six different indicators with different weights. The insolvency risk is evaluated based on the value of the DF indicator, assessing the total score to a certain level of solvency or insolvency. This model is complex and allows identifying possible solvency problems at an early stage.
3. A developed methodology for an insolvency risk assessment empirical research focuses on the identification of the most important macroeconomic factors, calculation of financial indicators, application of Kralicek DF indicator and bankruptcy prediction models.
4. Empirical research conducted using the data of companies listed on the NASDAQ Baltic stock exchange obtained the following results:
 - The analysis of the macroeconomic environment indicated that the main factors influencing the number of corporate insolvencies among the Baltic States are inflation and unemployment rates.
 - The analysis of financial indicators showed that more companies can be identified as a solvent than insolvent, however, there is an equal number of companies that are solvent and unprofitable, and

insolvent and unprofitable. All companies that are unprofitable have a higher risk to face financial distress.

- Insolvency risk assessment using the Kralicek DF indicator demonstrated that this model is suitable for companies, operating in the Baltic States. This model shows a precise level of assessment and help to identify at which stage of insolvency the company is.

- The application of bankruptcy prediction models indicated that not all of the models are suitable for the insolvency risk assessment as an additional tool. The models show different results on how many companies can be assessed as facing possible financial distress. For companies operating in the Baltic States worked the best such bankruptcy prediction models as Springate and Altman II.

- The comparison of the results obtained by the assessment of the financial ratios and the Kralicek DF indicator demonstrated certain differences. The main difference and limitation of financial ratios is the problem while assessing several ratios with different values, showing that from one point of view the company is solvent, however, in other segments there are potential risks. In this case, the reviewer's objectivity is also particularly important. As an additional tool at this stage, the Kralicek DF indicator is exceptionally valuable and a combination of those two methods shows more accurate results.

- The performed empirical research revealed that in the Baltic market around 50% of companies face solvency issues, which are usually enforced by the lack of working capital and negative operating and net cash flows. The main recommendation for companies would be the review of financial management policies, the identification of key problematic areas and searching for solutions to improve the cash flow situation.

- The main recommendation for investors or existing minority shareholders would be to constantly look for the financial information of a company and not underestimate the additional methods that could be used for an insolvency assessment.

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APPENDIX 1. Historical overview of bankruptcy models creation (Kubenka M., 2016)

Models used to predict financial distress	Researcher(s)	Year
Univariate models	Fitzpatrick	1931
	Ransmer and Foster	1931
	Merwin	1942
	Walter	1957
	Beaver	1966
Multivariate Discriminant Analysis (MDA)	Altman	1968
	Deakin	1972
	Edmister	1972
	Blum	1974
	Moyer	1977
	Altman, Halderman, and Narayanan	1977
	Altman	1983
	Booth	1983
	Fulmer, Moon, Gavin, and Erwin	1984
	Casey and Bartczak	1985
	Lawrence and Bear	1986
	Aziz, Emanuel, and Lawson	1988
	Altman	1993
	Altman	2000
Grice and Ingram	2001	
Logit and Probit Analysis	Martin	1977
	Ohlson	1980
	Rose and Giroux	1984
	Zavgren	1985
	Gentry, Newbold, and Whiteford	1985
	Lau	1987
	Platt and Platt	1990
	Koh	1991
	Lynn and Wertheim	1993
	Johnson and Melicher	1994
	Barniv, Hathorn, Megrez, and Kline	1999
	Lennox	1999
Recursive partitioning algorithms (RPA)	Marais, Patell, and Wolfson	1984
	Frydman, Altman, and Kao	1985
	Tam	1991
	McKee and Greenstein	2000
Artificial Neural Networks (ANN)	Odom and Sharda	1990
	Sachenberger, Cinar, and Lash	1992
	Coates and Fant	1991-1992
	Tam and Kiang	1992
	Coates and Fant	1993
	Nittayagasetwat	1994
	Serrano-Cinca	1996
	Lee, Han, and Kwon	1996
	Jo, Han, and Lee	1997
	Serrano-Cinca	1997
	Luther	1998
	Zhang, Hu, Patuwo, and Indro	1999
	Yang, Platt, and Platt	1999
	Shah and Murteza	2000

APPENDIX 2. Logit and probit analysis bankruptcy prediction models (designed according to Krusinskas R., 2014; Kovacova M, 2017; Freifalts M., 2018; Tanjung P., 2020; Sivolapenko E., 2020)

Author, accuracy	Formula	Characteristics of coefficients and their meaning	Bankruptcy probability assessment
Chesser (1974), *78%	$Z = -2,0434 - 5,24X1 + 0,0053X2 - 6,6507X3 + 4,4009X4 - 0,0791X5 - 0,1021X6$	X1 – cash / total assets X2 – net sales / cash X3 – earnings before interest and taxes / total assets X4 – total liabilities / total current X5 – long-term assets / equity X6 – working capital / net sales	High risk of bankrupt if PB > 50%
Ohlson (1980), *85%	$O = -1,32 - 0,407X1 + 6,03X2 - 1,43X3 + 0,0757X4 - 2,57X5 - 1,83X6 + 0,285X7 - 1,72X8 - 0,521X9$	X1 – Size (LOG (Total Assets/GNP Index)) X2 – Debt Ratio (Total Liabilities/Total Assets) X3 – Working Capital / Total Assets X4 – Current Liabilities to Current Assets X5 – Total Liabilities Exceeds Total Assets (OENEG) X6 – Return on Assets X7 – Funds Provided by Operations to Total Liabilities X8 – Net Income was Negative for The Last Two Years (INTWO) X9 – Delta Net Income Divided by the Sum of the Absolute Net Income (CHIN)	If O-Score > 0,38 financial distress companies If O-Score < 0,38 as non-financial distress companies
Zmijewski (1984), *99%	$X = -4,3 - 4,5X1 + 5,7X2 - 0,004X3$	X1 – net income / total assets X2 – total liabilities / total assets X3 – current assets / current liabilities	If X > 0 the company can be classified under unsanitary conditions or likely to lead to financial distress; If X < 0 then the company is classified in a healthy condition.

Author, accuracy	Formula	Characteristics of coefficients and their meaning	Bankruptcy probability assessment
Zavgren (1985), *82%	$Z1 = 0,11X1 + 1,5X2 + 10,78X3 - 3,07X4 - 0,49X5 + 4,35X6 - 0,11X7 - 0,24$ $Z2 = 4,19X1 + 2,22X2 + 11,23X3 - 2,69X4 - 1,44X5 + 4,46X6 + 0,06X7 - 2,61$ $Z3 = 6,257X1 + 0,829X2 + 42,48X3 - 1,549X4 + 0,519X5 + 1,822X6 + 0,0027X7 - 1,5115$ $Z4 = 9,157X1 + 1,667X2 + 5,917X3 - 0,41X4 + 1,95X5 + 4,1X6 + 0,363X7 - 5,9457$ $Z5 = 8,84X1 + 0,69X2 + 15,79X3 + 0,02X4 - 2,3X5 + 4,37X6 + 0,798X7 - 6,88$	X1 – inventories / net sales X2 – receivables / inventories X3 – cash / total assets X4 – quick assets / current liabilities X5 – sales / net plant where net plant=total assets – current liabilities X6 – debt / total capital X7 – total income / total capital	High risk of bankrupt if PB > 50%
A.Y. Belikov-G.V. Davydova (1999), *81%	$Z = 8.38K1 + K2 + 0.054K3 + 0.63K4$	K1 - Working capital / Assets K2 - Net profit / Equity K3 - Revenue / Assets K4 - Net profit / Operating Costs	Z more than 0.42, the risk of bankruptcy is minimal (up to 10%)
Grigaravicius (2003), *The more accurate, the shorter forecasting period	$Z = - 0,762 + 0,003X1 - 0,424X2 - 0,06X3 + 0,22X4 - 0,774X5 - 0,189X6 + 6,842X7 - 12,262X8 - 5,257X9$	X1 - Current assets / Current liabilities X2 - Net working capital / Total assets X3 - Total assets / Equity X4 - Equity / Financial liabilities X5 - Earnings before interest and taxes / Total assets X6 - Operating profit / Sales X7 - Net profit / Total assets X8 - Sales / Net working capital X9 - Sales / Total assets	On receipt of value Z, further the probability of bankruptcy is calculated using formula: $P = 1 / (1+e^{-z})$, bankruptcy probability is considered as high when value P exceeds 0.5

*Model prediction accuracy one year before bankruptcy

APPENDIX 3. Detailed list of analysed companies

No.	Ticker	Company name	MarketPlace	Sector
1	ARC1T	Arco Vara	Estonia	Real Estate
2	BLT1T	Baltika	Estonia	Consumer Products and Services
3	EEG1T	Ekspress Grupp	Estonia	Media
4	HAE1T	Harju Elekter	Estonia	Industrial Goods and Services
5	MRK1T	Merko Ehitus	Estonia	Construction and Materials
6	NCN1T	Nordecon	Estonia	Construction and Materials
7	PKG1T	Pro Kapital Grupp	Estonia	Real Estate
8	PRF1T	PRFoods	Estonia	Food, Beverage and Tobacco
9	SFG1T	Silvano Fashion Group	Estonia	Consumer Products and Services
10	SKN1T	Nordic Fibreboard	Estonia	Consumer Products and Services
11	TAL1T	Tallink Grupp	Estonia	Travel and Leisure
12	TKM1T	Tallinna Kaubamaja Grupp	Estonia	Retail
13	TSM1T	Tallinna Sadam	Estonia	Industrial Goods and Services
14	BAL1R	Latvijas balzams	Latvia	Food, Beverage and Tobacco
15	GZE1R	Latvijas Gāze	Latvia	Utilities
16	HMX1R	HansaMatrix	Latvia	Technology
17	LJM1R	Latvijas Jūras medicīnas centrs	Latvia	Health Care
18	OLF1R	Olainfarm	Latvia	Health Care
19	RAR1R	Rīgas autoelektroaparātu rūpnīca	Latvia	Real Estate
20	SAF1R	SAF Tehnika	Latvia	Telecommunications
21	SCM1R	Siguldas ciltslietu un mākslīgās apsēklošanas stacija	Latvia	Food, Beverage and Tobacco
22	AMG1L	Amber Grid	Lithuania	Energy
23	APG1L	Apranga	Lithuania	Retail
24	AUG1L	AUGA group	Lithuania	Food, Beverage and Tobacco
25	GRG1L	Grigeo	Lithuania	Basic Resources
26	IGN1L	Ignitis grupė	Lithuania	Utilities
27	KNF1L	Klaipėdos nafta	Lithuania	Industrial Goods and Services
28	KNR1L	Kauno energija	Lithuania	Utilities
29	LGD1L	LITGRID	Lithuania	Utilities
30	LNA1L	Linas Agro Group	Lithuania	Food, Beverage and Tobacco
31	LNS1L	Linas	Lithuania	Basic Resources
32	PTR1L	Panevėžio statybos trestas	Lithuania	Construction and Materials
33	PZV1L	Pieno žvaigždės	Lithuania	Food, Beverage and Tobacco
34	RSU1L	Rokiškio sūris	Lithuania	Food, Beverage and Tobacco
35	SNG1L	Snaigė	Lithuania	Consumer Products and Services
36	TEL1L	Telia Lietuva	Lithuania	Telecommunications
37	UTR1L	Utenos trikotažas	Lithuania	Consumer Products and Services
38	VBL1L	Vilniaus baldai	Lithuania	Consumer Products and Services
39	VLP1L	Vilkyškių pieninė	Lithuania	Food, Beverage and Tobacco
40	ZMP1L	Žemaitijos pienas	Lithuania	Food, Beverage and Tobacco

APPENDIX 4. Dynamics of macroeconomic indicators for 2018-2020 (designed by the author based on Statistics Lithuania, Statistics Estonia, Official statistics of Latvia)

Estonia							
	Y	X1	X2	X3	X4	X5	X6
2018	368.00	25,938.00	19,660.00	3.41	5.37	16,200.00	131,650.00
2019	402.00	28,112.00	21,220.00	2.27	5.12	20,072.22	133,784.00
2020	256.00	27,167.00	20,440.00	0.20	7.40	20,774.75	137,980.00
Latvia							
	Y	X1	X2	X3	X4	X5	X6
2018	593.00	29,143.00	15,130.00	2.55	7.41	15,792.00	174,792.00
2019	560.00	30,421.00	15,900.00	2.75	6.60	15,913.00	172,382.00
2020	374.00	29,334.00	15,430.00	0.57	8.20	15,105.00	175,362.00
Lithuania							
	Y	X1	X2	X3	X4	X5	X6
2018	2,090.00	45,491.00	16,200.00	2.53	6.10	30,942.00	104,117.00
2019	1,608.00	48,797.00	17,500.00	2.24	6.60	31,949.00	105,093.00
2020	786.00	48,793.00	17,458.00	1.28	9.20	28,969.00	107,444.00

APPENDIX 5. Solvency and liquidity ratios calculation

	Country	Sector	Current ratio			Quick ratio			Operating cash flow ratio			Debt-to-assets ratio			Debt-to-equity ratio		
			2018	2019	2020	2018	2019	2020	2018	2019	2020	2018	2019	2020	2018	2019	2020
Amber Grid	Lithuania	Energy	0.59	0.73	1.12	0.53	0.70	1.09	0.49	0.42	0.46	0.44	0.46	0.51	0.79	0.86	1.04
Apranga	Lithuania	Retail	2.70	1.44	1.93	0.62	0.31	0.89	0.78	0.93	1.08	0.28	0.62	0.60	0.39	1.61	1.53
Arco Vara	Estonia	Real Estate	1.25	1.80	2.72	0.19	0.15	0.52	-0.24	-0.16	-0.15	0.61	0.54	0.50	1.58	1.16	0.99
AUGA group	Lithuania	Food, Beverage and Tobacco	1.11	1.12	1.57	0.31	0.31	0.44	-0.21	0.10	0.32	0.47	0.56	0.57	0.88	1.30	1.31
Latvijas balzams	Latvia	Food, Beverage and Tobacco	2.54	3.45	3.30	1.94	2.79	2.57	0.23	1.14	0.20	0.26	0.20	0.21	0.35	0.26	0.27
Baltika	Estonia	Consumer Products and Services	0.87	0.76	0.81	0.13	0.13	0.29	-0.12	0.43	0.76	1.00	0.55	0.84	213.29	4.67	5.08
Ekspress Grupp	Estonia	Media	1.13	0.90	0.98	0.86	0.76	0.83	0.40	0.31	0.49	0.34	0.46	0.42	0.52	0.85	0.73
Grigeo	Lithuania	Basic Resources	0.95	1.13	1.56	0.62	0.80	1.23	0.75	0.86	0.97	0.42	0.34	0.27	0.73	0.52	0.38
Latvijas Gāze	Latvia	Utilities	3.22	4.16	3.76	1.22	2.70	2.60	0.42	2.32	0.99	0.25	0.17	0.17	0.33	0.21	0.21
Harju Elekter	Estonia	Industrial Goods and Services	1.71	1.46	1.42	1.03	0.89	0.88	-0.13	0.19	0.20	0.32	0.38	0.36	0.47	0.61	0.57
HansaMatrix	Latvia	Technology	1.02	0.85	0.77	0.50	0.49	0.53	0.33	0.25	0.16	0.65	0.70	0.70	1.89	2.33	2.31
Ignitis grupē	Lithuania	Utilities	1.16	0.86	3.19	1.04	0.76	3.08	0.47	0.36	0.91	0.54	0.58	0.54	1.24	1.42	1.15
Klaipėdos nafta	Lithuania	Industrial Goods and Services	4.75	1.27	1.47	4.65	1.24	1.43	1.35	1.06	0.79	0.33	0.71	0.67	0.50	2.48	2.01
Kauno energija	Lithuania	Utilities	1.58	1.03	0.86	1.47	0.92	0.75	0.75	0.66	0.86	0.39	0.42	0.45	0.65	0.72	0.82
LITGRID	Lithuania	Utilities	0.51	0.46	0.59	0.49	0.46	0.59	0.41	0.45	0.41	0.47	0.48	0.47	0.88	0.92	0.90
Latvijas Jūras medicīnas centrs	Latvia	Health Care	3.25	2.81	2.37	2.93	2.70	2.24	0.63	0.48	0.68	0.22	0.22	0.25	0.29	0.29	0.32
Linās Agro Group	Lithuania	Food, Beverage and Tobacco	1.38	1.26	1.31	0.79	0.71	0.74	-0.11	0.11	0.22	0.56	0.57	0.55	1.28	1.32	1.25
Linās	Lithuania	Basic Resources	3.46	3.11	5.35	1.32	0.80	2.73	0.20	0.02	0.81	0.22	0.23	0.26	0.28	0.30	0.34
Merko Ehitus	Estonia	Construction and Materials	2.22	2.84	2.68	1.13	1.19	1.06	0.32	-0.13	0.81	0.49	0.52	0.39	1.01	1.13	0.65
Nordecon	Estonia	Construction and Materials	1.12	1.01	1.01	0.75	0.69	0.75	0.09	0.12	0.03	0.68	0.72	0.72	2.22	2.79	2.63
Olainfarm	Latvia	Health Care	1.65	3.09	1.21	0.98	2.02	0.00	0.41	1.34	1.12	0.29	0.24	0.24	0.41	0.32	0.32
Pro Kapital Grupp	Estonia	Real Estate	2.37	0.42	0.63	0.34	0.10	0.10	-0.04	0.16	-0.07	0.59	0.66	0.92	1.47	1.96	11.83
PRFoods	Estonia	Food, Beverage and Tobacco	1.10	0.89	0.82	0.63	0.28	0.27	-0.02	0.16	0.21	0.63	0.65	0.65	1.77	1.91	1.92
Panevėžio statybos trestas	Lithuania	Construction and Materials	1.91	1.63	0.75	1.26	0.85	0.53	-0.27	-0.50	0.03	0.44	0.54	0.63	0.80	1.21	1.72
Pieno žvaigždės	Lithuania	Food, Beverage and Tobacco	0.92	1.12	1.14	0.50	0.61	0.50	0.47	0.54	0.67	0.64	0.61	0.54	1.81	1.56	1.18
Rīgas autoelektroaparātu rūpnīca	Latvia	Real Estate	0.42	0.23	0.22	0.26	0.12	0.09	-0.19	-0.15	0.28	0.53	0.53	0.51	1.11	1.14	1.06
Rokiškio sūris	Lithuania	Food, Beverage and Tobacco	2.92	3.18	2.70	1.44	1.41	1.14	-0.60	-0.07	0.04	0.23	0.23	0.26	0.31	0.29	0.36
SAF Tehnika	Latvia	Telecommunications	6.67	4.49	3.15	3.51	2.02	1.54	-0.53	-0.02	0.72	0.14	0.28	0.36	0.16	0.40	0.57
Siguldas ciltslietu un mākslīgās apsēklošanas stacija	Latvia	Food, Beverage and Tobacco	14.00	14.11	12.08	6.00	5.78	5.42	0.08	0.67	1.11	0.06	0.06	0.07	0.06	0.06	0.07
Silvano Fashion Group	Estonia	Consumer Products and Services	2.35	2.67	3.37	1.16	0.76	1.26	0.76	1.49	0.72	0.33	0.36	0.34	0.54	0.63	0.52
Nordic Fibreboard	Estonia	Consumer Products and Services	1.11	0.32	0.74	0.39	0.20	0.44	0.16	0.07	0.09	0.72	0.83	0.65	2.56	4.87	1.89
Snaigē	Lithuania	Consumer Products and Services	0.61	0.50	1.13	0.44	0.30	0.63	0.02	0.03	0.00	0.77	0.79	0.78	3.42	3.74	3.48
Tallink Grupp	Estonia	Travel and Leisure	0.79	0.54	0.42	0.62	0.38	0.29	0.74	0.79	-0.03	0.43	0.46	0.53	0.75	0.86	1.12
Telia Lietuva	Lithuania	Telecommunications	1.36	1.16	1.11	1.28	1.09	1.03	1.02	1.07	1.01	0.43	0.47	0.46	0.76	0.87	0.84
Tallinna Kaubamāja Grupp	Estonia	Retail	1.13	1.00	0.83	0.46	0.42	0.32	0.46	0.48	0.48	0.45	0.56	0.63	0.82	1.29	1.68
Tallinna Sadam	Estonia	Industrial Goods and Services	1.51	1.48	1.23	1.50	1.47	1.21	1.70	2.03	1.63	0.41	0.40	0.40	0.70	0.66	0.67
Utenos trikotažas	Lithuania	Consumer Products and Services	1.22	1.46	1.37	0.61	0.58	0.77	0.04	0.40	0.39	0.50	0.52	0.55	1.02	1.11	1.26
Vilniaus baldai	Lithuania	Consumer Products and Services	1.31	0.69	0.85	0.73	0.26	0.48	0.37	0.27	0.23	0.57	0.66	0.70	1.32	1.95	2.37
Vilkyškių pieninė	Lithuania	Food, Beverage and Tobacco	0.81	0.72	0.64	0.29	0.34	0.29	0.11	0.09	0.23	0.62	0.60	0.55	1.61	1.51	1.20
Zemaitijos pienas	Lithuania	Food, Beverage and Tobacco	2.08	3.12	3.26	0.97	1.52	1.66	0.41	0.78	0.89	0.29	0.31	0.26	0.42	0.45	0.35

APPENDIX 6. Profitability ratios calculation

	Country	Sector	ROA			ROE			Net profit margin			EBIT margin		
			2018	2019	2020	2018	2019	2020	2018	2019	2020	2018	2019	2020
Amber Grid	Lithuania	Energy	-8.38	4.82	6.35	-0.16	0.09	0.12	-0.40	0.22	0.36	0.27	0.26	0.27
Apranga	Lithuania	Retail	9.53	7.97	3.15	0.13	0.16	0.08	0.04	0.05	0.03	0.05	0.06	0.05
Arco Vara	Estonia	Real Estate	-1.88	1.25	3.55	-0.04	0.03	0.07	-0.15	0.03	0.07	-0.05	0.07	0.12
AUGA group	Lithuania	Food, Beverage and Tobacco	-3.72	-1.71	0.84	-0.07	-0.04	0.02	-0.11	-0.05	0.02	-0.12	0.00	0.07
Latvijas balzams	Latvia	Food, Beverage and Tobacco	6.37	6.49	5.70	0.08	0.08	0.07	0.12	0.13	0.14	0.10	0.11	0.11
Baltika	Estonia	Consumer Products and Services	-31.18	-27.93	-1.72	-73.14	-1.85	-0.14	-0.11	-0.15	-0.02	-0.04	-0.08	0.04
Ekspress Grupp	Estonia	Media	0.01	1.62	2.65	0.00	0.03	0.05	0.00	0.02	0.04	0.02	0.04	0.04
Grigeo	Lithuania	Basic Resources	12.18	11.65	11.09	0.21	0.18	0.15	0.10	0.10	0.10	0.09	0.11	0.11
Latvijas Gāze	Latvia	Utilities	6.20	4.61	2.43	0.08	0.05	0.03	0.07	0.06	0.06	0.06	0.05	0.05
Harju Elekter	Estonia	Industrial Goods and Services	1.64	2.39	4.98	0.02	0.04	0.08	0.01	0.02	0.04	0.02	0.02	0.04
HansaMatrix	Latvia	Technology	3.55	0.78	-1.67	0.09	0.02	-0.05	0.04	0.01	-0.02	0.07	0.06	0.03
Ignitis grupė	Lithuania	Utilities	-0.84	1.87	4.74	-0.02	0.04	0.09	-0.02	0.05	0.14	0.01	0.08	0.19
Klaipėdos nafta	Lithuania	Industrial Goods and Services	3.90	1.58	5.16	0.06	0.04	0.16	0.12	0.07	0.42	0.11	0.13	0.27
Kauno energija	Lithuania	Utilities	2.69	0.75	0.40	0.04	0.01	0.01	0.07	0.02	0.01	0.06	0.00	0.01
LITGRID	Lithuania	Utilities	-9.77	1.24	6.72	-0.20	0.02	0.12	-0.23	0.02	0.13	-0.09	-0.03	0.15
Latvijas Jūras medicīnas centrs	Latvia	Health Care	0.48	2.31	3.82	0.01	0.03	0.05	0.00	0.02	0.04	-0.01	0.01	0.04
Linus Agro Group	Lithuania	Food, Beverage and Tobacco	2.40	-1.25	2.45	0.05	-0.03	0.05	0.01	-0.01	0.01	0.01	0.00	0.02
Linus	Lithuania	Basic Resources	4.84	1.01	4.56	0.06	0.01	0.06	0.04	0.01	0.04	0.03	-0.01	0.01
Merko Ehitus	Estonia	Construction and Materials	7.08	5.90	8.54	0.15	0.12	0.15	0.05	0.05	0.07	0.04	0.05	0.08
Nordecon	Estonia	Construction and Materials	3.13	3.05	3.30	0.11	0.11	0.03	0.02	0.01	0.00	0.01	0.02	0.01
Olainfarm	Latvia	Health Care	7.29	14.93	5.60	0.10	0.19	0.07	0.09	0.17	0.08	0.12	0.20	0.13
Pro Kapital Grupp	Estonia	Real Estate	8.01	-11.84	-29.10	0.17	-0.38	-4.01	0.60	-0.49	-2.98	0.10	0.16	-2.13
PRFoods	Estonia	Food, Beverage and Tobacco	2.00	-2.28	-2.87	0.00	-0.07	-0.09	0.00	-0.02	-0.02	0.01	-0.01	-0.01
Panevėžio statybos trestas	Lithuania	Construction and Materials	-5.97	0.58	-12.75	-0.11	0.01	-0.36	-0.04	0.00	-0.13	-0.02	-0.01	-0.14
Pieno žvaigždės	Lithuania	Food, Beverage and Tobacco	2.96	5.57	10.49	0.08	0.14	0.23	0.01	0.02	0.05	0.01	0.02	0.05
Rīgas autoelekroaparātu rūpnīca	Latvia	Real Estate	-2.90	-3.32	-0.86	-0.06	-0.07	-0.02	-5.50	-12.00	-0.27	-5.00	-11.00	-0.91
Rokiškio sūris	Lithuania	Food, Beverage and Tobacco	1.15	2.42	2.22	0.01	0.03	0.03	0.01	0.02	0.02	0.01	0.02	0.02
SAF Tehnika	Latvia	Telecommunications	-1.65	-3.35	3.05	-0.02	-0.04	0.04	-0.02	-0.03	0.03	0.00	-0.04	0.03
Siguldas ciltslietu un mākslīgās apsūklošanas stacija	Latvia	Food, Beverage and Tobacco	-0.68	3.18	6.27	-0.01	0.03	0.06	-0.01	0.05	0.09	0.04	0.11	0.16
Silvano Fashion Group	Estonia	Consumer Products and Services	21.95	23.23	5.30	0.39	0.41	0.09	0.17	0.19	0.07	0.29	0.23	0.27
Nordic Fibreboard	Estonia	Consumer Products and Services	-8.39	-14.45	14.00	-0.31	-0.91	0.40	-0.06	-0.11	0.10	-0.04	-0.05	0.00
Snaigė	Lithuania	Consumer Products and Services	-1.37	-6.00	0.63	-0.06	-0.31	0.03	-0.01	-0.05	0.01	-0.03	-0.05	0.01
Tallink Grupp	Estonia	Travel and Leisure	2.62	3.28	-6.10	0.05	0.06	-0.15	0.04	0.05	-0.24	0.07	0.08	-0.21
Telia Lietuva	Lithuania	Telecommunications	9.68	9.29	9.14	0.17	0.17	0.17	0.15	0.14	0.14	0.17	0.16	0.17
Tallinna Kaubamaja Grupp	Estonia	Retail	7.53	6.67	3.48	0.13	0.14	0.09	0.04	0.04	0.03	0.05	0.06	0.04
Tallinna Sadam	Estonia	Industrial Goods and Services	4.00	7.11	4.55	0.07	0.12	0.08	0.19	0.34	0.27	0.40	0.40	0.32
Utenos trikotažas	Lithuania	Consumer Products and Services	5.57	3.25	-1.96	0.10	0.07	-0.04	0.04	0.02	-0.02	0.05	0.03	0.03
Vilniaus baldai	Lithuania	Consumer Products and Services	7.10	8.59	7.12	0.14	0.21	0.20	0.03	0.05	0.07	0.03	0.03	0.06
Vilkyškių pieninė	Lithuania	Food, Beverage and Tobacco	-1.45	-0.56	5.00	-0.04	-0.01	0.11	-0.01	0.00	0.03	-0.01	0.00	0.04
Žemaitijos pienas	Lithuania	Food, Beverage and Tobacco	9.93	9.04	7.70	0.13	0.13	0.10	0.06	0.06	0.05	0.05	0.06	0.06

APPENDIX 7. The assessment of companies by group

	Profitable	Unprofitable
Solvent	Latvijas balzams	Linās
	Grigeo	Utenos trikotažas
	Merko Ehitus	AUGA group
	Silvano Fashion Group	Linās Agro Group
	Amber Grid	Rokiškio sūris
	Siguldas ciltslietu un mākslīgās apsēklošanas stacija	Latvijas Jūras medicīnas centrs
	Žemaitijos pienas	Harju Elekter
	Olainfarm	Ekspress Grupp
	Klaipēdos nafta	Arco Vara
	Tallinna Sadam	Apranga
	Telia Lietuva	SAF Tehnika
	Latvijas Gāze	Kauno energija
	Ignitis grupē	LITGRID
Insolvent	Vilniaus baldai	Baltika
		HansaMatrix
		Nordecon
		Pro Kapital Grupp
		PRFoods
		Panēvēžio stатыbos trestas
		Pieno žvaigždēs
		Rīgas autoelektroaparātu rūpnīca
		Nordic Fibreboard
		Snaigē
		Tallink Grupp
		Tallinna Kaubamaja Grupp
	Vilkyškių pieninė	

APPENDIX 10. Zmijewski score calculation, figures in mil. EUR

	2018										2019										2020									
	Net income	Total assets	Total liabilities	Current assets	Current liabilities	X1	X2	X3	Zmijewski Score		Net income	Total assets	Total liabilities	Current assets	Current liabilities	X1	X2	X3	Zmijewski Score		Net income	Total assets	Total liabilities	Current assets	Current liabilities	X1	X2	X3	Zmijewski Score	
Amber Grid	-21.59	235.42	103.82	28.3	48.02	-0.09	0.44	0.59	-1.38	11.84	256.13	118.28	46.78	64.2	0.05	0.46	0.73	-1.88	18.17	316.37	161.54	60.61	54.04	0.06	0.51	1.12	-1.65			
Apranga	7.57	79.1	22.34	52.75	19.55	0.10	0.28	2.70	-3.13	9.24	152.79	94.24	51.08	35.51	0.06	0.62	1.44	-1.06	4.94	160.3	96.82	65.63	33.96	0.03	0.60	1.93	-1.00			
Arco Vara	-0.54	33.52	20.51	20.62	16.53	-0.02	0.61	1.25	-0.74	0.39	28.75	15.46	17.22	9.55	0.01	0.54	1.80	-1.30	1.01	28.23	14.01	18.5	6.79	0.04	0.50	2.72	-1.64			
AUGA group	-5.96	171.89	80.18	59.95	54.14	-0.03	0.47	1.11	-1.49	-3.23	206.72	116.65	62.05	55.33	-0.02	0.56	1.12	-1.02	1.77	213.7	120.89	66.11	41.98	0.01	0.57	1.57	-1.12			
Latvijas balzams	9.39	153.76	39.64	90.1	35.45	0.06	0.26	2.54	-3.12	10.05	156.02	31.85	101.51	29.4	0.06	0.20	3.45	-3.44	9.32	169.98	36.48	114.9	34.83	0.05	0.21	3.30	-3.34			
Baltika	-5.12	15	14.93	12	13.76	-0.34	1.00	0.87	2.91	-5.91	27.32	14.93	8.56	11.23	-0.22	0.55	0.76	-0.21	-0.38	16.48	13.77	5.21	6.4	-0.02	0.84	0.81	0.56			
Ekspress Grupp	0.01	76.74	26.3	13.83	12.19	0.00	0.34	1.13	-2.35	1.39	95.41	43.79	19.47	21.65	0.01	0.46	0.90	-1.75	2.51	94.18	39.56	18.48	18.95	0.03	0.42	0.98	-2.03			
Grigeo	14.06	115.35	48.46	32.81	34.36	0.12	0.42	0.95	-2.46	13.51	116.52	39.65	34.07	30.02	0.12	0.34	1.13	-2.89	13.29	123.18	33.63	42.82	27.42	0.11	0.27	1.56	-3.24			
Latvijas Gāze	25.19	412.48	102.12	167.34	52.04	0.06	0.25	3.22	-3.18	20.19	464.24	80.53	143.04	34.38	0.04	0.17	4.16	-3.52	11.19	455.55	79.71	136.35	36.22	0.02	0.17	3.76	-3.43			
Harju Elekter	1.55	98.15	31.21	44	25.73	0.02	0.32	1.71	-2.57	2.46	107.9	40.92	48.01	32.96	0.02	0.38	1.46	-2.25	5.56	115.48	42.08	49.75	34.98	0.05	0.36	1.42	-2.45			
HansaMatrix	0.78	25.35	16.58	7.34	7.2	0.03	0.65	1.02	-0.71	0.21	29.81	20.78	7.31	8.61	0.01	0.70	0.85	-0.36	-0.46	28.05	19.58	6.33	8.19	-0.02	0.70	0.77	-0.25			
Ignitis grupē	-22.44	2853.89	1,551.37	442.88	382.66	-0.01	0.54	1.16	-1.17	56.67	3198.09	1,849.47	427.53	499.01	0.02	0.58	0.86	-1.09	169.82	3969.3	2,125.47	986.56	309.3	0.04	0.54	3.19	-1.45			
Klaipēdos nafta	11.58	293.13	97.64	90.1	18.98	0.04	0.33	4.75	-2.60	7.56	663.3	472.65	81.95	64.29	0.01	0.71	1.27	-0.29	33.96	651.69	435.37	91.7	62.27	0.05	0.67	1.47	-0.73			
Kauno energija	4	148.27	58.3	22.97	14.56	0.03	0.39	1.58	-2.19	1.14	154.1	64.27	14.31	13.9	0.01	0.42	1.03	-1.96	0.63	162.9	73.23	10.73	12.48	0.00	0.45	0.86	-1.76			
LITGRID	-39.36	366.26	171.23	32.29	63.74	-0.11	0.47	0.51	-1.15	4.61	377.37	180.63	25.51	54.97	0.01	0.48	0.46	-1.63	26.6	414.35	196.32	38.97	66.12	0.06	0.47	0.59	-1.89			
Latvijas Jūras medicīnas centrs	0.03	7.11	1.58	2.44	0.75	0.00	0.22	3.25	-3.07	0.16	7.08	1.58	2.42	0.86	0.02	0.22	2.81	-3.14	0.27	7.08	1.75	2.56	1.08	0.04	0.25	2.37	-3.07			
Linās Agro Group	9.04	400.94	223.86	260.56	188.66	0.02	0.56	1.38	-1.22	-4.96	391.4	221.33	242.37	191.87	-0.01	0.57	1.26	-1.02	9.75	405.42	224.22	233.03	177.39	0.02	0.55	1.31	-1.26			
Linās	0.51	10.6	2.35	7.06	2.04	0.05	0.22	3.46	-3.27	0.11	10.88	2.52	7.44	2.39	0.01	0.23	3.11	-3.04	0.51	11.67	2.98	8.56	1.6	0.04	0.26	5.35	-3.06			
Merko Ehitus	19.34	269.66	133.32	234.38	105.4	0.07	0.49	2.22	-1.81	16.27	281.83	147.27	281.83	99.1	0.06	0.52	2.84	-1.59	22.99	256.92	99.48	206.78	77.04	0.09	0.39	2.68	-2.51			
Nordecon	3.38	104.14	70.43	61.13	54.46	0.03	0.68	1.12	-0.60	3.38	117.65	84.88	67.55	66.85	0.03	0.72	1.01	-0.32	1.25	135.04	97.8	87.69	86.47	0.01	0.72	1.01	-0.22			
Olainfarm	10.73	147.91	42.83	63.12	38.16	0.07	0.29	1.65	-2.98	23.63	168.67	41.16	79.7	25.79	0.14	0.24	3.09	-3.55	9.48	171.62	41.25	30.93	25.54	0.06	0.24	1.21	-3.18			
Pro Kapital Grupp	16.83	245.11	144.37	69.3	29.18	0.07	0.59	2.37	-1.26	-26.98	210.82	139.26	53.12	125.9	-0.13	0.66	0.42	0.04	-57.28	183.38	169.09	69.54	110.55	-0.31	0.92	0.63	2.36			
PRFoods	0.057	65.49	41.23	29.84	27.03	0.00	0.63	1.10	-0.72	-1.46	62.53	40.67	24.79	27.84	-0.02	0.65	0.89	-0.49	-1.72	57.12	37.31	17.99	21.95	-0.03	0.65	0.82	-0.44			
Panevėžio statybos trestas	-3.69	64.05	28.14	51.48	26.91	-0.06	0.44	1.91	-1.54	0.41	76.68	41.44	65.71	40.24	0.01	0.54	1.63	-1.25	-9.5	72.39	45.25	32.68	43.39	-0.13	0.63	0.75	-0.15			
Pieno žvaigždės	2.2	73.47	47.34	29.38	31.83	0.03	0.64	0.92	-0.77	4.11	74.01	45.12	25.1	22.46	0.06	0.61	1.12	-1.08	7.71	73.05	39.61	23.5	20.59	0.11	0.54	1.14	-1.69			
Rīgas autoelekroaparātu rūpnīca	-0.11	3.79	1.99	0.08	0.19	-0.03	0.53	0.42	-1.18	-0.12	3.59	1.91	0.06	0.26	-0.03	0.53	0.23	-1.12	-0.03	3.4	1.75	0.05	0.23	-0.01	0.51	0.22	-1.33			
Rokiškio sūris	1.92	170.21	39.89	106.07	36.28	0.01	0.23	2.92	-3.03	4.1	169.07	38.3	106.77	33.53	0.02	0.23	3.18	-3.13	4.06	197.07	51.64	120.42	44.65	0.02	0.26	2.70	-2.91			
SAF Tehnika	-0.22	11.48	1.6	10.67	1.6	-0.02	0.14	6.67	-3.45	-0.41	13.23	3.76	11.01	2.45	-0.03	0.28	4.49	-2.56	0.44	15.56	5.65	13.36	4.24	0.03	0.36	3.15	-2.37			
Siguldas ciļstlietu un mākslīgās apsēkšanas stacija	-0.01	1.57	0.09	1.26	0.09	-0.01	0.06	14.00	-4.00	0.05	1.59	0.09	1.27	0.09	0.03	0.06	14.11	-4.18	0.1	1.73	0.12	1.45	0.12	0.06	0.07	12.08	-4.21			
Silvano Fashion Group	10.8	45.5	14.89	34.9	14.83	0.24	0.33	2.35	-3.51	10.66	46.31	16.56	27.12	10.15	0.23	0.36	2.67	-3.31	2.55	42.25	14.44	29.59	8.78	0.06	0.34	3.37	-2.64			
Nordic Fibreboard	-0.89	10.31	7.41	3.45	3.1	-0.09	0.72	1.11	0.18	-1.4	9.05	7.5	2.3	7.23	-0.15	0.83	0.32	1.12	1.07	7.65	5.002	1.36	1.85	0.14	0.65	0.74	-1.21			
Snaigē	-0.41	30.65	23.72	12.43	20.38	-0.01	0.77	0.61	0.17	-1.69	25.53	20.14	8.75	17.5	-0.07	0.79	0.50	0.49	0.16	24.8	19.26	9.47	8.4	0.01	0.78	1.13	0.09			
Tallink Grupp	40.05	1500.9	643.99	167.85	212.49	0.03	0.43	0.79	-1.98	49.72	1532.96	710.13	120.61	221.44	0.03	0.46	0.54	-1.81	-108.3	1516.2	801.87	88.34	208.34	-0.07	0.53	0.42	-0.97			
Telia Lietuva	54.7	564.11	244.33	141.65	104.49	0.10	0.43	1.36	-2.27	54.73	614.12	286.04	151.52	130.12	0.09	0.47	1.16	-2.05	55.87	608.45	276.94	144.95	130.54	0.09	0.46	1.11	-2.12			
Tallinna Kaubamāja Grupp	30.44	411.08	185.46	131.54	116.78	0.07	0.45	1.13	-2.07	31.14	522.31	294.48	135.84	136.28	0.06	0.56	1.00	-1.36	19.5	597.28	374.28	125.99	152.24	0.03	0.63	0.83	-0.88			
Tallinna Sadam	24.42	623.64	255.97	50.89	33.68	0.04	0.41	1.51	-2.14	44.4	625.53	248.51	46.35	31.27	0.07	0.40	1.48	-2.36	28.52	628.09	252.66	37.34	30.47	0.05	0.40	1.23	-2.22			
Ūtenos trikotāžas	1.11	22.21	11.05	11.7	9.61	0.05	0.50	1.22	-1.69	0.73	22.94	11.97	11.03	7.58	0.03	0.52	1.46	-1.47	-0.45	23.23	12.82	12.43	9.09	-0.02	0.55	1.37	-1.07			
Vilniaus baldai	2.26	36.75	20.9	15.96	12.16	0.06	0.57	1.31	-1.34	4.07	58.02	38.32	11.93	17.26	0.07	0.66	0.69	-0.85	5.03	83.24	58.55	15.35	17.99	0.06	0.70	0.85	-0.57			
Vilkyskių pieninė	-1.19	82.29	50.74	23.73	29.17	-0.01	0.62	0.81	-0.72	-0.45	78.05	46.94	20.84	28.75	-0.01	0.60	0.72	-0.85	3.87	76.9	41.93	21.67	33.99	0.05	0.55	0.64	-1.42			
Žemaitijos pienas	10.64	114.17	33.04	58.11	27.94	0.09	0.29	2.08	-3.08	10.82	125.18	38.47	62.9	20.17	0.09	0.31	3.12	-2.95	9.8	129.42	33.11	69.67	21.4	0.08	0.26	3.26	-3.20			

APPENDIX 11. Grover score calculation, figures in mil. EUR

	2018										2019										2020									
	Working capital	Total assets	EBIT	ROA, %	Current assets	Current liabilities	X1	X2	Grover Score	Working capital	Total assets	EBIT	ROA, %	Current assets	Current liabilities	X1	X2	Grover Score	Working capital	Total assets	EBIT	ROA, %	Current assets	Current liabilities	X1	X2	Grover Score			
Amber Grid	-19.72	235.42	14.48	-8.38	28.3	48.02	-0.08	0.06	0.13	-17.42	256.13	13.73	4.82	46.78	64.2	-0.07	0.05	0.13	6.57	316.37	13.59	6.35	60.61	54.04	0.02	0.04	0.24			
Apranga	33.2	79.1	10.19	9.53	52.75	19.55	0.42	0.13	1.04	15.57	152.79	12.84	7.97	51.08	35.51	0.10	0.08	0.51	31.67	160.3	9.15	3.15	65.63	33.96	0.20	0.06	0.58			
Arco Vara	4.09	33.52	-0.17	-1.88	20.62	16.53	0.12	-0.01	0.27	7.67	28.75	0.94	1.25	17.22	9.55	0.27	0.03	0.61	11.71	28.23	1.73	3.55	18.5	6.79	0.41	0.06	0.95			
AUGA group	5.81	171.89	-6.66	-3.72	59.95	54.14	0.03	-0.04	0.04	6.72	206.72	0.27	-1.71	62.05	55.33	0.03	0.00	0.12	24.13	213.7	5.55	0.84	66.11	41.98	0.11	0.03	0.33			
Latvijas balzams	54.65	153.76	7.71	6.37	90.1	35.45	0.36	0.05	0.71	72.11	156.02	8.34	6.49	101.51	29.4	0.46	0.05	1.00	80.07	169.98	7.39	5.7	114.9	34.83	0.47	0.04	0.98			
Baltika	-1.76	15	-1.72	-31.18	12	13.76	-0.12	-0.11	-0.03	-2.67	27.32	-3.2	-27.93	8.56	11.23	-0.10	-0.12	-0.50	-1.19	16.48	0.74	-1.72	5.21	6.4	-0.07	0.04	0.09			
Ekspress Grupp	1.64	76.74	1.04	0.01	13.83	12.19	0.02	0.01	0.14	-2.18	95.41	2.43	1.62	19.47	21.65	-0.02	0.03	0.11	-0.47	94.18	2.56	2.65	18.48	18.95	0.00	0.03	0.14			
Grigeo	-1.55	115.35	13.43	12.18	32.81	34.36	-0.01	0.12	0.24	4.05	116.52	15.5	11.65	34.07	30.02	0.03	0.13	0.57	15.4	123.18	14.74	11.09	42.82	27.42	0.13	0.12	0.67			
Latvijas Gāze	115.3	412.48	20.13	6.2	167.34	52.04	0.28	0.05	0.59	108.66	464.24	17.03	4.61	143.04	34.38	0.23	0.04	0.57	100.13	455.55	10.18	2.43	136.35	36.22	0.22	0.02	0.50			
Harju Elekter	18.27	98.15	2.49	1.64	44	25.73	0.19	0.03	0.42	15.05	107.9	3.31	2.39	48.01	32.96	0.14	0.03	0.39	14.77	115.48	6.55	4.98	49.75	34.98	0.13	0.06	0.46			
HansaMatrix	0.14	25.35	1.54	3.55	7.34	7.2	0.01	0.06	0.22	-1.3	29.81	1.41	0.78	7.31	8.61	-0.04	0.05	0.15	-1.86	28.05	0.57	-1.67	6.33	8.19	-0.07	0.02	0.02			
Ignitis grupē	60.22	2,853.89	11.89	-0.84	442.88	382.66	0.02	0.00	0.12	-71.48	3,198.09	86.89	1.87	427.53	499.01	-0.02	0.03	0.11	677.26	3,969.30	233.44	4.74	986.56	309.3	0.17	0.06	0.54			
Klaipēdos nafta	71.12	293.13	11.3	3.9	90.1	18.98	0.24	0.04	0.53	17.66	663.3	14.01	1.58	81.95	64.29	0.03	0.02	0.17	29.43	651.69	21.62	5.16	91.7	62.27	0.05	0.03	0.24			
Kauno enerģija	8.41	148.27	3.75	2.69	22.97	14.56	0.06	0.03	0.19	0.41	154.1	-0.02	0.75	14.31	13.9	0.00	0.00	0.06	-1.75	162.9	0.3	0.4	10.73	12.48	-0.01	0.00	0.05			
LITGRID	-31.45	366.26	-14.48	-9.77	32.29	63.74	-0.09	-0.04	-0.06	-29.46	377.37	-6.31	1.24	25.51	54.97	-0.08	-0.02	-0.13	-27.15	414.35	30.25	6.72	38.97	66.12	-0.07	0.07	0.20			
Latvijas Jūras medicīnas centrs	1.69	7.11	-0.1	0.48	2.44	0.75	0.24	-0.01	0.39	1.56	7.08	0.05	2.31	2.42	0.86	0.22	0.01	0.44	1.48	7.08	0.27	3.82	2.56	1.08	0.21	0.04	0.53			
Linas Agro Group	71.9	400.94	8.97	2.4	260.56	188.66	0.18	0.02	0.39	50.5	391.4	-2.8	-1.25	242.37	191.87	0.13	-0.01	0.25	55.64	405.42	14.62	2.45	233.03	177.39	0.14	0.04	0.41			
Linas	5.02	10.6	0.35	4.84	7.06	2.04	0.47	0.03	0.87	5.05	10.88	-0.1	1.01	7.44	2.39	0.46	-0.01	0.79	6.96	11.67	0.13	4.56	8.56	1.6	0.60	0.01	1.08			
Merko Ehitus	128.98	269.66	17.11	7.08	234.38	105.4	0.48	0.06	0.95	182.73	281.83	16.74	5.9	281.83	99.1	0.65	0.06	1.33	129.74	256.92	23.72	8.54	206.78	77.04	0.50	0.09	1.20			
Nordecon	6.67	104.14	3.02	3.13	61.13	54.46	0.06	0.03	0.21	0.7	117.65	4.1	3.05	67.55	66.85	0.01	0.03	0.18	1.22	135.04	3.6	3.3	87.69	86.47	0.01	0.03	0.16			
Olainfarm	24.96	147.91	15.35	7.29	63.12	38.16	0.17	0.10	0.57	53.91	168.67	27.54	14.93	79.7	25.79	0.32	0.16	1.14	5.39	171.62	15.77	5.6	30.93	25.54	0.03	0.09	0.42			
Pro Kapital Grupp	40.12	245.11	2.81	8.01	69.3	29.18	0.16	0.01	0.24	-72.78	210.82	9.1	-11.84	53.12	125.9	-0.35	0.04	-0.36	-41.01	183.38	-40.93	-29.1	69.54	110.55	-0.22	-0.22	-1.07			
PRFoods	2.81	65.49	1.49	2	29.84	27.03	0.04	0.02	0.17	-3.05	62.53	-0.45	-2.28	24.79	27.84	-0.05	-0.01	-0.05	-3.96	57.12	-0.91	-2.87	17.99	21.95	-0.07	-0.02	-0.11			
Panevėžio statybos trestas	24.57	64.05	-1.83	-5.97	51.48	26.91	0.38	-0.03	0.69	25.47	76.68	-0.87	0.58	65.71	40.24	0.33	-0.01	0.57	-10.71	72.39	-10.24	-12.75	32.68	43.39	-0.15	-0.14	-0.67			
Pieno žvaigždės	-2.45	73.47	1.99	2.96	29.38	31.83	-0.03	0.03	0.05	2.64	74.01	4.14	5.57	25.1	22.46	0.04	0.06	0.31	2.91	73.05	8.76	10.49	23.5	20.59	0.04	0.12	0.53			
Rīgas autoelekroaparātu rūpnīca	-0.11	3.79	-0.1	-2.9	0.08	0.19	-0.03	-0.03	-0.03	-0.2	3.59	-0.11	-3.32	0.06	0.26	-0.06	-0.03	-0.14	-0.18	3.4	-0.1	-0.86	0.05	0.23	-0.05	-0.03	-0.13			
Rokiškio sūris	69.79	170.21	1.28	1.15	106.07	36.28	0.41	0.01	0.74	73.24	169.07	3.42	2.42	106.77	33.53	0.43	0.02	0.84	75.77	197.07	4.58	2.22	120.42	44.65	0.38	0.02	0.77			
SAF Tehnika	9.07	11.48	0.04	-1.65	10.67	1.6	0.79	0.00	1.40	8.56	13.23	-0.51	-3.35	11.01	2.45	0.65	-0.04	0.99	9.12	15.56	0.47	3.05	13.36	4.24	0.59	0.03	1.13			
Siguldas ciltslietu un mākslīgās apsūkšanas stacija	1.17	1.57	0.04	-0.68	1.26	0.09	0.75	0.03	1.38	1.18	1.59	0.12	3.18	1.27	0.09	0.74	0.08	1.54	1.33	1.73	0.18	6.27	1.45	0.12	0.77	0.10	1.68			
Silvano Fashion Group	20.07	45.5	17.97	21.95	34.9	14.83	0.44	0.39	1.78	16.97	46.31	12.99	23.23	27.12	10.15	0.37	0.28	1.61	20.81	42.25	10.54	5.3	29.59	8.78	0.49	0.25	1.72			
Nordic Fibreboard	0.35	10.31	-0.64	-8.39	3.45	3.1	0.03	-0.06	0.04	-4.93	9.05	-0.69	-14.45	2.3	7.23	-0.54	-0.08	-1.10	-0.49	7.65	-0.02	14	1.36	1.85	-0.06	0.00	-0.06			
Snaigē	-7.95	30.65	-1.1	-1.37	12.43	20.38	-0.26	-0.04	-0.47	-8.75	25.53	-1.47	-6	8.75	17.5	-0.34	-0.06	-0.70	1.07	24.8	0.32	0.63	9.47	8.4	0.04	0.01	0.17			
Tallink Grupp	-44.64	1,500.90	63.77	2.62	167.85	212.49	-0.03	0.04	0.11	-100.83	1,532.96	75.1	3.28	120.61	221.44	-0.07	0.05	0.11	-120	1516.2	-92.62	-6.1	88.34	208.34	-0.08	-0.06	-0.28			
Telia Lietuva	37.16	564.11	65.57	9.68	141.65	104.49	0.07	0.12	0.41	21.4	614.12	62.43	9.29	151.52	130.12	0.03	0.10	0.46	14.41	608.45	66.69	9.14	144.95	130.54	0.02	0.11	0.47			
Tallinna Kaubamāja Grupp	14.76	411.08	37.33	7.53	131.54	116.78	0.04	0.09	0.30	-0.44	522.31	40.44	6.67	135.84	136.28	0.00	0.08	0.32	-26.25	597.28	28.01	3.48	125.99	152.24	-0.04	0.05	0.14			
Tallinna Sadam	17.21	623.64	52.16	4	50.89	33.68	0.03	0.08	0.32	15.08	625.53	51.77	7.11	46.35	31.27	0.02	0.08	0.38	6.87	628.09	34.17	4.55	37.34	30.47	0.01	0.05	0.26			
Utenos trikotāžas	2.09	22.21	1.47	5.57	11.7	9.61	0.09	0.07	0.35	3.45	22.94	0.77	3.25	11.03	7.58	0.15	0.03	0.42	3.34	23.23	0.93	-1.96	12.43	9.09	0.14	0.04	0.43			
Vilniaus baldai	3.8	36.75	2.35	7.1	15.96	12.16	0.10	0.06	0.33	-5.33	58.02	2.08	8.59	11.93	17.26	-0.09	0.04	0.03	-2.64	83.24	4.05	7.12	15.35	17.99	-0.03	0.05	0.17			
Vilkyškių pieninė	-5.44	82.29	-1.06	-1.45	23.73	29.17	-0.07	-0.01	-0.07	-7.91	78.05	-0.28	-0.56	20.84	28.75	-0.10	0.00	-0.12	-12.32	76.9	4.29	5	21.67	33.99	-0.16	0.06	-0.02			
Zemaitijos pienas	30.17	114.17	9.7	9.93	58.11	27.94	0.26	0.08	0.62	42.73	125.18	11.48	9.04	62.9	20.17	0.34	0.09	0.93	48.27	129.42	11.33	7.7	69.67	21.4	0.37	0.09	0.97			

APPENDIX 12. Altman II score calculation, figures in mil. EUR

	2018															2019															2020														
	Working capital	Total assets	Retained earnings	Operating profit	Equity	Liabilities	Revenue	X1	X2	X3	X4	X5	Altman II Score	Working capital	Total assets	Retained earnings	Operating profit	Equity	Liabilities	Revenue	X1	X2	X3	X4	X5	Altman II Score	Working capital	Total assets	Retained earnings	Operating profit	Equity	Liabilities	Revenue	X1	X2	X3	X4	X5	Altman II Score						
Amber Grid	-19.72	235.42	-20.48	14.48	131.60	103.82	53.92	-0.08	-0.09	0.06	1.27	0.23	0.82	-17.42	256.13	11.48	13.73	137.85	118.28	53.69	-0.07	0.04	0.05	1.17	0.21	0.85	6.57	316.37	13.59	154.83	161.54	50.49	0.02	0.09	0.04	0.96	0.16	0.79							
Apranga	33.20	79.10	39.18	10.19	56.76	22.34	186.79	0.42	0.50	-0.13	2.54	2.36	4.54	15.57	152.79	40.96	12.84	58.55	94.24	204.63	0.10	0.27	0.08	0.62	1.34	2.16	31.67	160.30	45.90	9.15	63.48	96.82	169.58	0.20	0.29	0.06	0.66	1.06	1.89						
Arco Vara	4.09	33.52	2.16	-0.17	13.00	20.51	3.64	0.12	0.06	-0.01	0.63	0.11	0.50	7.67	28.75	2.46	0.94	13.30	15.46	13.11	0.27	0.09	0.03	0.86	0.46	1.18	11.71	28.23	3.36	1.73	14.22	14.01	14.06	0.41	0.12	0.06	1.01	0.50	1.51						
AUGA group	5.81	171.89	8.94	-6.66	91.36	80.18	54.75	0.03	0.05	-0.04	1.14	0.32	0.74	6.72	206.72	5.10	0.27	89.71	116.65	71.13	0.03	0.02	0.00	0.77	0.34	0.71	24.13	213.70	6.24	5.55	92.45	120.89	83.07	0.11	0.03	0.03	0.76	0.39	0.90						
Latvijas balzams	54.65	153.76	101.22	7.71	114.12	39.64	75.14	0.36	0.66	0.05	2.88	0.49	2.67	72.11	156.02	111.27	8.34	124.17	31.85	78.56	0.46	0.71	0.05	3.90	0.50	3.24	80.07	169.98	120.59	7.39	133.50	36.48	68.62	0.47	0.71	0.04	3.66	0.40	3.01						
Baltika	-1.76	15.00	-5.12	-1.72	0.07	14.93	44.69	-0.12	-0.34	-0.11	0.00	2.98	2.25	-2.67	27.32	-6.25	-3.20	3.20	14.93	39.71	-0.10	-0.23	-0.12	0.21	1.45	0.91	-1.19	16.48	-6.63	0.74	2.71	13.77	19.73	-0.07	-0.40	0.04	0.20	1.20	1.02						
Ekspress Grupp	1.64	76.74	16.53	1.04	50.35	26.30	60.49	0.02	0.22	0.01	1.91	0.79	1.83	-2.18	95.41	17.70	2.43	51.52	43.79	67.46	-0.02	0.19	0.03	1.18	0.71	1.42	-0.47	94.18	20.19	2.56	54.49	39.56	63.24	0.00	0.21	0.03	1.38	0.67	1.51						
Grigeo	-1.55	115.35	46.38	13.43	66.24	48.46	142.55	-0.01	0.40	0.12	1.37	1.24	2.50	4.05	116.52	55.99	15.50	76.25	39.65	140.27	0.03	0.48	0.13	1.92	1.20	2.85	15.40	123.18	69.28	14.74	88.96	33.63	129.60	0.13	0.56	0.12	2.65	1.05	3.10						
Latvijas Gāze	115.30	412.48	107.04	20.13	310.36	102.12	344.90	0.28	0.26	0.05	3.04	0.84	2.68	108.66	464.24	111.88	17.03	383.71	80.53	314.35	0.23	0.24	0.04	4.76	0.68	3.16	100.13	455.55	111.17	10.18	375.84	79.71	190.49	0.22	0.24	0.02	4.72	0.42	2.83						
Harju Elekter	18.27	98.15	52.32	2.49	66.96	31.21	120.80	0.19	0.53	0.03	2.15	1.23	2.79	15.05	107.90	51.70	3.31	67.09	40.92	143.40	0.14	0.48	0.03	1.64	1.33	2.62	14.77	115.48	54.86	6.55	73.55	42.08	146.61	0.13	0.48	0.06	1.75	1.27	2.67						
HansaMatrix	0.14	25.35	2.34	1.54	8.77	16.58	21.15	0.01	0.09	0.06	0.53	0.83	1.33	-1.30	29.81	2.61	1.41	8.91	20.78	24.61	-0.04	0.09	0.05	0.43	0.83	1.19	-1.86	28.05	2.29	0.57	8.47	19.58	22.66	-0.07	0.08	0.02	0.43	0.81	1.07						
Ignitis grupē	60.22	2853.89	-169.99	11.89	1254.96	1551.37	1024.28	0.02	-0.06	0.00	0.81	0.36	0.68	-71.48	3198.09	-172.19	86.89	1299.62	1849.47	1073.01	-0.02	-0.05	0.03	0.70	0.34	0.65	677.26	3969.30	-86.16	233.44	1842.36	2125.47	1215.36	0.17	-0.02	0.06	0.87	0.31	0.96						
Klaipēdas nafta	71.12	293.13	11.58	11.30	195.49	97.64	100.00	0.24	0.04	0.04	2.00	0.34	1.51	17.66	663.30	7.42	14.01	190.65	472.65	104.36	0.03	0.01	0.02	0.40	0.16	0.42	29.43	651.69	33.21	21.62	216.33	435.37	80.11	0.05	0.05	0.03	0.50	0.12	0.51						
Kauno enerģija	8.41	148.27	8.96	3.75	89.97	58.30	61.32	0.06	0.06	0.03	1.54	0.41	1.23	0.41	154.10	5.00	-0.02	89.83	64.27	54.65	0.00	0.03	0.00	1.40	0.35	0.97	-1.75	162.90	4.85	0.30	89.67	73.23	42.03	-0.01	0.03	0.00	1.22	0.26	0.80						
LITGRID	-31.45	366.26	-38.62	-14.48	195.03	171.23	169.76	-0.09	-0.11	-0.04	1.14	0.46	0.67	-29.46	377.37	4.13	-6.31	196.74	180.63	184.68	-0.08	0.01	-0.02	1.09	0.49	0.85	-27.15	414.35	25.43	30.25	218.04	196.32	206.40	-0.07	0.06	0.07	1.11	0.50	1.20						
Latvijas Jūras medicīnas centrs	1.69	7.11	2.06	-0.10	5.53	1.58	6.67	0.24	0.29	-0.01	3.50	0.94	2.78	1.56	7.08	2.03	0.05	5.50	1.58	7.27	0.22	0.29	0.01	3.48	1.03	2.91	1.48	7.08	1.32	0.27	5.52	1.75	7.08	0.21	0.19	0.04	3.15	1.00	2.75						
Linas Agro Group	71.90	400.94	102.95	8.97	174.99	223.86	634.42	0.18	0.26	-0.02	0.78	1.58	2.32	50.50	391.40	89.96	-2.80	168.01	221.33	742.54	0.13	0.23	-0.01	0.76	1.90	2.48	55.64	405.42	105.12	14.62	178.95	224.22	657.70	0.14	0.26	0.04	0.80	1.62	2.38						
Linas	5.02	10.60	1.11	0.35	8.25	2.35	12.71	0.47	0.10	0.03	3.51	1.20	3.20	5.05	10.88	0.91	-0.10	8.36	2.52	12.98	0.46	0.08	-0.01	3.32	1.19	2.96	6.96	11.67	1.59	0.13	8.79	2.98	14.01	0.60	0.14	0.01	2.92	1.20	3.00						
Merko Ehitus	128.98	269.66	123.76	17.11	131.76	133.32	418.01	0.48	0.46	0.06	0.99	1.55	2.89	182.73	281.83	122.33	16.74	130.34	147.27	326.78	0.65	0.43	0.06	0.89	1.16	2.55	129.74	256.92	145.32	23.72	153.23	99.48	315.92	0.50	0.57	0.09	1.54	1.23	3.00						
Nordecon	6.67	104.14	10.90	3.02	31.69	70.43	223.50	0.06	0.10	0.03	0.45	2.15	2.56	0.70	117.65	12.38	4.10	30.46	84.88	234.07	0.01	0.11	0.03	0.36	1.99	2.34	1.22	135.04	14.54	3.60	37.24	97.80	296.08	0.01	0.11	0.03	0.38	1.19	2.53						
Olainfarm	24.96	147.91	83.08	15.35	105.08	42.83	124.26	0.17	0.56	0.10	2.45	0.84	2.79	53.91	168.67	105.30	27.54	127.51	41.16	137.22	0.32	0.62	0.16	3.10	0.81	3.38	5.39	171.62	89.95	15.77	130.42	41.25	122.16	0.03	0.52	0.09	3.16	0.71	2.79						
Pro Kapital Grupp	40.12	245.11	76.77	2.81	98.11	144.37	27.99	0.16	0.31	0.01	0.68	0.11	0.82	-72.78	210.82	49.74	9.10	71.14	139.26	55.28	-0.35	0.24	0.04	0.51	0.26	0.56	-41.01	183.38	49.74	-40.93	14.28	169.09	19.23	-0.22	0.27	-0.22	0.08	0.10	-0.48						
PRFoods	2.81	65.49	2.13	1.49	23.30	41.23	118.49	0.04	0.03	0.02	0.57	1.81	2.17	-3.05	62.53	0.07	-0.45	21.26	40.67	85.73	-0.05	0.00	0.01	0.52	1.37	1.53	-3.96	57.12	-1.65	-0.91	19.39	37.31	78.29	-0.07	-0.03	-0.02	0.52	1.37	1.46						
Panvežīo stātybos trestas	24.57	64.05	23.78	-1.83	34.96	28.14	104.86	0.38	0.37	-0.03	1.24	1.64	2.66	25.47	76.68	24.34	-0.87	34.33	41.44	110.47	0.33	0.32	-0.01	0.83	1.44	2.26	-10.71	72.39	14.59	-10.24	26.33	45.25	74.91	-0.15	0.20	-0.14	0.58	1.03	0.90						
Pieno švaigzdes	-2.45	73.47	2.95	1.99	26.13	47.34	168.66	-0.03	0.04	0.03	0.55	2.30	2.62	2.64	74.01	6.34	4.14	28.89	45.12	170.60	0.04	0.09	0.06	0.64	2.31	2.84	2.91	73.05	10.89	8.76	33.44	39.61	171.06	0.04	0.15	0.12	0.84	2.34	3.22						
Rīgas autociekroapārāru rūpnīca	-0.11	3.79	-3.27	-0.10	1.80	9.99	0.02	-0.03	-0.86	-0.03	0.90	0.01	-0.45	-0.20	3.59	-3.40	-0.11	1.68	1.91	0.01	-0.06	-0.95	-0.03	0.88	0.00	-0.57	-0.18	3.40	-3.43	-0.10	1.65	1.75	0.11	-0.05	-1.01	-0.03	0.94	0.03	-0.56						
Rokiškio sūris	69.79	170.21	75.71	1.28	130.32	39.89	203.68	0.41	0.44	0.01	3.27	1.20	3.26	73.24	169.07	78.56	3.42	130.77	38.30	208.37	0.43	0.46	0.02	3.41	1.23	3.43	75.77	197.07	80.64	4.58	145.43	51.64	210.83	0.38	0.41	0.02	2.82	1.07	2.94						
SAF Tehnika	9.07	11.48	2.86	0.04	9.88	1.60	13.41	0.79	0.25	0.00	6.18	1.17	4.55	8.56	13.23	2.44	-0.51	9.47	3.76	14.44	0.65	0.18	-0.04	2.52	1.09	2.65	9.12	15.56	2.88	0.47	9.91	5.65													